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Abstract

This paper offers a descriptive empirical analysis of the geographic pattern of income inequality within a sample of 359 US metropolitan areas between 1980 and 2000. Specifically, we decompose the variance of metropolitan area-level household income into two parts: one associated with the degree of variation among household incomes within neighborhoods - defined by block groups and tracts - and the other associated with the extent of variation among households in different neighborhoods. Consistent with previous work, the results reveal that the vast majority of a city's overall income inequality - at least three quarters - is driven by within-neighborhood variation rather than between-neighborhood variation, although we find that the latter rose significantly during the 1980s, especially between block groups. We then identify a number of metropolitan area-level characteristics that are associated with both levels of and changes in the degree of each type of residential income inequality.

JEL Classification: D31, R23, J10

Keywords: Income Inequality, Residential Segregation, Neighborhoods

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1 Introduction

Over the past three decades, income inequality has risen dramatically in the United States. Figures reported by the US Census Bureau, for example, indicate that the variance of the log household income distribution increased by nearly 25 percent between 1970 and 2000.[1] The rather striking nature of this rise has, of course, attracted a sizable literature which has both documented many of the trends and offered a variety of possible explanations.[2]

What this research has not done, for the most part, is explore the residential aspects of this trend. That is, most of the existing inequality literature has not looked at whether the growth of income dispersion has been accompanied by increasing residential segregation by income. In light of the significance of neighborhood-level influences (including the income of one's neighbors) on a variety of economic behaviors and outcomes, we believe that income segregation across residential areas is an issue that deserves considerable study.[3]

This paper offers a purely empirical look at some trends in neighborhood-level income inequality, defined by the variation exhibited by average household incomes among a collection of roughly 165000 block groups and 50000 tracts in 359 US metropolitan areas, over the years 1980, 1990, and 2000. In particular, our interest is focused on documenting the evolution of income dispersion both within these neighborhoods as well as between them and then evaluating whether several of the mechanisms the inequality literature has identified as influencing overall inequality have been equally important in affecting inequality within and between neighborhoods. The results reveal a number of interesting patterns.

First, the majority of income inequality is associated with inequality within block groups and tracts. In each year, more than 75 percent of a typical metropolitan area's income variation can be linked to income variation among households living in the same block group. When examining tracts, more than 80 percent can be tied to within-neighborhood

[1] These numbers are available at http://www.census.gov/hhes/income/histinc/ie6.html.

[2] A brief sampling of the literature appears in the next section.

[3] The literature on neighborhood effects, which have been shown to influence employment status, income, and criminal behavior among other outcomes, is quite extensive. See Durlauf (2004) for a survey.

income differences.

Second, between 1980 and 2000, income inequality increased both between neighborhoods and within them. On average, metropolitan areas experienced a 10 log point increase in the variance of their household income distributions over these two decades. Within- and between-block group variation increased by, respectively, 5 and 6 log points whereas within- and between-tract variation increased by, respectively, 8 and 2 log points.

Third, the decade of the 1980s saw a particularly large rise in the degree of inequality between different neighborhoods, especially block groups. The fraction of the average metropolitan area's total income variance attributable to between-block group differences in average incomes rose from 13 percent to 21 percent during this decade. Between-tract differences rose from 13 percent of total income variation in 1980 to 16 percent in 1990. Both figures, however, decreased slightly between 1990 and 2000.

Fourth, results from a series of simple regressions suggest that a number of city-level characteristics that previous work has found to be important in explaining overall income inequality (e.g. the unemployment rate, the level of education, the fraction of the local population that is foreign-born or black) show differential associations with the two types of income variation. For example, the unemployment rate tends to show a significant association with the degree of income variation across different neighborhoods, but not with income variation within neighborhoods. On the other hand, the fraction of highly educated workers (a proxy for the presence of skill-biased technologies) tends to vary significantly with inequality both within and between neighborhoods.

Because income gaps across residential areas may perpetuate inequality over time through neighborhood-level influences (e.g. interactions with peers, local school quality; see Durlauf (1996)), we speculate that some mechanisms - namely, those that exacerbate between-neighborhood income differentials - might have more lasting effects on inequality than others.

The remainder of the paper proceeds as follows. The next section reviews some relevant literature in order to compare our results to those of existing studies and, thus, clarify our contribution. Section 3 then provides a brief description of the data and measurement techniques, particularly the decomposition of overall income variation into within- and between-neighborhood components. Section 4 reports the results from the analysis of these components. Section 5 concludes.

2 A Survey of Related Research

This paper touches on a number of existing literatures. Most obviously, it relates to a massive body of work that has looked at the rise in both income and earnings inequality in the US over recent decades. This research has documented some of the more salient trends and discussed a variety of potential explanations including rising returns to skill (e.g. Juhn et al. (1993)), increasing use of computer technologies in the workplace (e.g. Autor et al. (1998)), institutional changes such as a declining minimum wage (e.g. Lee (1999)) and a decreasing rate of unionization (e.g. Fortin and Lemieux (1997)), changing industrial structure (e.g. Bernard and Jensen (2000)), and the rising globalization of markets implied by growing levels of trade and immigration (e.g. Borjas (2003), Card (1990), Butcher and Card (1991)). As noted above, however, this literature has not considered the geographic aspects of the issue, particularly those involved with neighborhood-level patterns within cities.

With respect to residential segregation, a relatively large literature spanning several decades has explored the separation of individuals based on race or ethnicity. Duncan and Duncan (1955), Taeuber and Taeuber (1965), Jakubs (1986), Massey and Denton (1988), and Cutler et al. (1999) are just a few prominent examples of this work. While it is certainly true that race tends to be correlated with income, these studies do not directly address the issue of income inequality either across or within neighborhoods.

There have been, for several decades, studies looking at the differential economic outcomes experienced by central cities and their surrounding suburban areas. Mayer (1996), for example, finds that families living below the poverty level became increasingly concentrated in US inner cities between 1964 and 1994.[4] Pack (2002) shows that, between 1970 and 1990, per capita income in the suburban parts of the nation's metropolitan areas tended to grow more rapidly than that of their corresponding central cities so that, by 1990, suburban per capita income exceeded central city per capita income throughout the country. Because they are concerned with a center-periphery view of metropolitan areas, however, these studies do not provide any sense of the extent of income segregation within or between small neighborhoods.

Some existing research, by contrast, has explored patterns of income inequality across Census tracts in US cities and metropolitan areas, yet the focus of this work has usually been on the concentration of poverty. Kasarda (1993) and Abramson et al. (1995), for example, have both examined the extent to which individuals who live in poverty reside in relatively poor tracts. In general, they find increases in the extent to which the poor live amongst themselves between 1970 and 1990, at least within the largest cities and metropolitan areas in the country. This evidence, however, focuses on the bottom end of the income distribution and, so, provides little indication either about patterns of overall inequality or the degree to which total income variation has changed between and within neighborhoods.

There are several papers that, following the theoretical literature on Tiebout sorting, have explored the degree of heterogeneity among the residents of small neighborhoods. Ioannides (2004) and Hardman and Ioannides (2004), for example, use data from the American Housing Survey to examine the degree of dependence between the incomes of households located within small clusters of housing units. These clusters include approximately 700 to 1000 individual residential units and roughly 10 of their 'nearest neighbors.' Ioannides and Seslen (2002) employ this same data along with the Panel Survey of Income Dynamics to

[4] Madden (2000) finds a similar result using household income within US metropolitan areas between 1980 and 1990.

measure wealth and income inequality at varying levels of residential aggregation, including small neighborhood clusters and metropolitan areas.

Among other things, this research concludes that, although there is a strong correlation between the income and wealth of neighboring households, there remains a substantial amount of heterogeneity within those neighborhood clusters. However, much like the research on concentrated poverty discussed above, these papers do not provide an overall sense of the extent to which income inequality within a metropolitan area can be attributed to income differentials within or between residential areas. The nature of the American Housing Survey, which reports information for only a limited number of housing units (700 to 1000 nationwide between 1985 and 1993), of course, makes this type of exercise difficult.

What is undoubtedly most closely related to our current study is a series of papers that has quantified economic segregation among U.S. Census tracts. These analyses (e.g. Massey and Eggers (1990), Jargowsky (1996), Mayer (2001), Yang and Jargowsky (2006)) have documented trends in the extent of income differences across residential areas within the last several decades. As with the work cited above, these papers have found that, in any given year, the majority of overall income inequality is associated with differences among households within neighborhoods rather than differences between neighborhoods (i.e. segregation). However, Jargowsky (1996) and Mayer (2001) find that segregation increased dramatically between 1980 and 1990, while Yang and Jargowsky (2006) report that it declined during the 1990s.

In this paper, we follow much the same methodological approach as these papers, but our focus is somewhat different. In particular, we are interested in documenting trends in each of three measures of income inequality – total, between-neighborhood, within-neighborhood – rather than segregation (usually based on the ratio of between to total), and do so at both the block group and tract levels. We also attempt to explore some basic determinants of the within and between measures. What types of metropolitan areas, for example, have witnessed particularly large increases in their within- and between-neighborhood income differentials? Are characteristics that are correlated with one type of inequality correlated with the other as well? We attempt to provide some answers to these questions.

3 Data

3.1 Sources and Measurement

A number of data sources are used in the analysis. Data on household income at the block group and tract levels comes from GeoLytics, who have compiled data from the 1980, 1990, and 2000 US Census of Population and Housing using fixed geographic definitions.[5] Hence, we are able to estimate mean household income within small neighborhoods whose boundaries are constant over time.

There are two fundamental geographic units that we consider: block groups and tracts. Block groups are the smaller of the two. Across the 359 metro areas in the sample, there are roughly 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. The sample also includes approximately 50000 tracts which, in 2000, averaged 1648.8 households and had a median land area of 1.31 square miles.

Due to their smaller size, block groups are our preferred units of analysis. Neighborhoods, ideally, should capture spaces over which individuals can reasonably be expected to interact with one another. Clearly, this expectation is more likely to be satisfied among groups of 500 households spread out over a third of a square mile than an area more than three times as large.[6] Nevertheless, although we focus on block groups for much of the paper, we feel that, for the sake of comparison, it is appropriate to conduct the analysis on tracts as well.

We estimate the variance of a metropolitan area's income distribution as follows. For

[5]These data are described at http://www.geolytics.com.

[6]Hardman and Ioannides (2004) express a similar preference for neighborhoods defined at the sub-tract level based on the idea that many interactions are likely to take place within particularly small areas.

each year, the number of households with incomes falling into each of N closed intervals is reported.[7] We use these figures to compute the fraction of households with incomes less than N distinct quantities which allow us estimate N quantiles of the household income distribution for each metro area. For example, if 14 percent of all households have income less than 25000 dollars, we estimate the 0.14 quantile by 25000. Label these quantiles X_α. We 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.

We consider the following standard decomposition. The variance of log household income in a metropolitan area, σ^2, can be estimated as

[7] 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.

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

where $y_{h,n}$ is the income of household h in neighborhood n, $\bar{y}$ is the mean household income for the 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, $\sum_n H_n$.[8] This expression can be re-written as the sum of two terms:

$$\sigma^2 = \frac{1}{H}\sum_{n=1}^{N}\sum_{h=1}^{H_n}(y_{h,n} - \bar{y}_n)^2 + \frac{1}{H}\sum_{n=1}^{N}\sum_{h=1}^{H_n}(\bar{y}_n - \bar{y})^2 \tag{3}$$

where $\bar{y}_n$ represents the mean household income in neighborhood n. The first of the terms on the right-hand-side of (3) is the 'within' neighborhood component, which measures the degree of income dispersion among households residing in the same neighborhood. The second term, the 'between' component, captures the amount of income variation across different neighborhoods.

Since we do not have data for individual households, we are unable to compute the within component directly.[9] However, we are able to estimate the between component and the variance, σ^2, which then permits us to form an estimate of within-neighborhood income variation as the difference between the two. This is essentially the same approach Jargowsky (1996) employs. We also generated a pseudo-direct measure of within-neighborhood inequality using the income interval data reported for each block group. To do so, we simply used the same procedure as that outlined above. The results (not reported) were very similar to

[8]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 (2) instead of $\frac{1}{H-1}$ is extremely small.

[9]Our lack of household-level data also prevents us from calculating the Theil index, which is a widely used metric for quantifying inequality that can be separated into between- and within-group components.

what we do report.[10]

We augment these inequality measures with a variety of data, most of which is derived from the US Census, describing some of the demographic and economic characteristics of the corresponding metropolitan areas. These quantities are discussed in greater detail below.

3.2 Basic Block Group Inequality Patterns

We begin by looking at some residential inequality trends based on block groups. Summary statistics describing overall, within-block group, and between-block group inequality for the 359 US metropolitan areas in the sample appear in Table 1. Two features are particularly apparent. First, the majority of a typical metropolitan area's household income inequality is associated with variation among households living in the same block group. In each year, within-neighborhood inequality accounts for more than three quarters of the total variance in household income. Recall, this finding is qualitatively similar to the results of Ioannides (2004), Hardman and Ioannides (2004), and Ioannides and Seslen (2002) who find substantial income and wealth heterogeneity among small clusters of housing units. It is also consistent with those of Epple and Sieg (1999), who report that within-municipality inequality can account for roughly 89 percent of the overall income inequality observed in Boston in 1980, and Jargowsky's (1996) results on income segregation across US Census tracts between 1970 and 1990.

Second, income inequality has shown an upward trend over the sample time frame. All three measures (overall income variance, between-neighborhood variation, and within-neighborhood variation) grew between 1980 and 2000, with the majority of this growth taking place during the 1980s. This result, of course, matches the well-documented rise in income disparity in the US over this period.

[10]The correlation between the two measures of within-block group income variation was 0.9. The resulting fractions of total income variation due to the within-neighborhood component using this alternative estimation method were very similar to what appears in Table 1: 0.875 in 1980, 0.808 in 1990, and 0.816 in 2000.

Here, however, we can see some basic geographic aspects of this rise. In particular, although the increase in overall inequality was associated with an increase in both the extent of dispersion within block groups as well as between them, the majority of the increase in income variance came from the latter. Between 1980 and 2000, the average metro area income variance rose by 10 log points. Nearly 60 percent of this increase can be linked to rising between-neighborhood income differences. Of course, all of this increase came during the 1980s when the extent of income variation between block groups rose by 7 log points.

A similar qualitative result emerges when we compute between-neighborhood income inequality by percentile differences rather than using the decomposition above. To do so, we calculate the 90th, 50th, and 10th percentiles of distribution of (log) average household income among block groups within each metropolitan area, where we weight each block group by its share of the total number of households in the metropolitan area. We then take differences among these three quantiles. Between 1980 and 1990, the average 90-10 difference rose from 0.633 to 0.874, but then declined to 0.867 in 2000. These changes were relatively evenly divided across the top and bottom of the income distribution. The 90-50 and 50-10 gaps both increased by roughly 0.12 during the 1980s, but then dropped slightly during the 1990s.

To gain a better sense of how much the change in a metropolitan area's total income variation can be attributed to each component, we calculated the ratio of the change in a metropolitan area's within-block group inequality over each decade to its corresponding change in total income inequality. Doing so provides an estimate of the fraction of the change in overall inequality associated with each component. The median values across the 359 metro areas in the sample indicate that, during the 1980s, roughly 67 percent of the change in total income inequality can be linked to changes in between-block group income differentials.[11] This finding, recall, is loosely compatible with the evidence surveyed in Section 2 that poverty became more concentrated during the 1980s.

[11] We report medians instead of means because the resulting shares had a few extreme outliers.

The subsequent decade, however, was very different. Between 1990 and 2000, the vast majority of a typical metropolitan area's change in overall inequality was associated with within-block group changes. Only 27 percent of the change in total income variation within a metro area over this decade can be tied to changing between-block group gaps.

Tables 2A, 2B, and 2C list the top and bottom 15 metropolitan areas according to each measure of inequality averaged over the three Census years. Based purely on the decomposition, cities with high levels of either within-neighborhood or between-neighborhood inequality are likely to have high levels of overall inequality, and we see this pattern from some of the overlap in the tables. For example, College Station-Bryan, TX has high levels of both overall inequality and within-neighborhood inequality; Los Angeles-Long Beach-Santa Ana, CA has high levels of overall inequality and between-neighborhood inequality. Not surprisingly, the correlations between metropolitan area-level income variance and both the level of within-neighborhood inequality and between-neighborhood inequality are high, respectively 0.77 and 0.8.

Indeed, one might suspect that all three measures of inequality would be strongly correlated, and there are certainly instances in Tables 2A-2C that seem to bear out this conclusion. The metro area with the highest average level of household income variation between 1980 and 2000, for instance, Bridgeport-Stamford-Norwalk, CT, also had the highest level of between-neighborhood inequality and the fourth highest level of within-neighborhood inequality. New York-Northern New Jersey-Long Island, NY-NJ-PA also appears near the top of all three measures of inequality. Conversely, Fond du Lac and Sheboygan, both in Wisconsin, each rank among the metropolitan areas with the lowest inequality levels in terms of all three measures.

However, metropolitan areas with particularly high levels of within-neighborhood income variation are not necessarily the same as those with particularly high levels of between-neighborhood variation. For example, although Morgantown, WV has a level of within-neighborhood inequality that is the fifth highest in the country, its level of between-neighborhood inequality ranks 217th. Memphis, TN-MS-AR has the fourth highest average level of between-neighborhood inequality, but only ranks 223rd in within-neighborhood income variance. In fact, the correlation between these two types of inequality turns out to be rather modest (although significantly different from zero), 0.24. When looking at 10-year differences in each measure of inequality, the correlation is statistically negligible, -0.004.

These findings suggest that the mechanisms underlying the rise of inequality within neighborhoods may not be the same as those underlying the rise of inequality between neighborhoods. In the next section, we explore this idea further.

4 Empirical Analysis - Determinants of Inequality

4.1 Theoretical Explanations

We begin our empirical investigation with a brief description of some explanations for why income inequality might differ across metropolitan areas. Given the rise in inequality within the US over the last three decades, a host of theories have been proposed for changes in overall income dispersion. Below, we sketch six commonly suggested hypotheses and attempt to relate them to the level of inequality observed between and within neighborhoods.

First, inequality may have risen in recent decades as a result of technological change that favors highly skilled individuals. Increasingly, workplace technologies (e.g. computer equipment) have be designed to boost the productivity and earnings of workers at the top of the income distribution (Autor et al. (1998, 2003)). One plausible reason for this change, quite simply, is the rise in the supply of skilled (e.g. highly educated) workers. Acemoglu (1998), for instance, argues that, as skilled (e.g. college-educated) workers have become more plentiful in the economy, employers have had greater incentives to adopt technologies that complement these types of workers. This process may have produced a widening gap between what skilled and unskilled workers earn.

Second, inequality may depend on the demographic makeup of the households living within an economy. Female, single, and non-white households, for example, tend to have relatively low incomes, as do younger households. A larger presence of these types of individuals, then, may be associated with an expanding lower tail of the income distribution and, thus, a rise in the amount of overall income dispersion we observe in a metropolitan area.[12] Similarly, older households tend to be characterized by greater levels of income variability (Deaton and Paxson (1997)), presumably because older workers have been on potentially divergent income paths for longer. Cities with larger fractions of older households, then, may exhibit greater inequality.

Third, the earnings of low-skill workers may have been eroded by the rise in the number of immigrant workers into the country, many of whom take jobs that pay relatively low wages. This is a relatively straightforward supply-side explanation. If, given a particular technology in a city-level economy, the number of low-skill workers increases, the earnings of those workers should tend to decline, all else held constant. Admittedly, the evidence on this hypothesis is mixed. Borjas (2003), for example, finds significantly negative effects of immigration on domestic wages whereas Card (1990) and Butcher and Card (1991) do not.[13] Nevertheless, the presence of immigrant labor is a possibility that we consider in the analysis below.

Fourth, changes in labor market institutions, such as a decrease in the rate of unionization, might also have an effect on the relative incomes of workers. Although the earnings premium associated with union coverage might, in theory, increase wage dispersion between union and non-union workers, research has largely shown that unionization tends, overall, to have an equalizing effect on earnings (e.g. Bernard and Jensen (2000)).

Fifth, technological change and rising international trade have produced economic shifts

[12] To be sure, these relationships would only hold for a certain range of values. Once these groups become a majority of the population, the income distribution may become less spread out as these households become more numerous.

[13] In his survey of the topic, Topel (1997) suggests that the preponderance of the evidence indicates that immigration has little impact on inequality.

that have likely affected the average labor earnings of workers at certain points of the income distribution more than those of workers at other points. The decline of manufacturing in particular has been widely cited as a driving mechanism behind the run-up in US income inequality because manufacturing has historically been associated with relatively high levels of compensation for workers with relatively low levels of education (e.g. Bound and Johnson (1992), Wilson (1997), Bernard and Jensen (2000)).

Sixth, the extent of income dispersion may also depend on the state of the business cycle. Blank (1989), for instance, has shown that the incomes of households at the low end of the distribution tend to be more sensitive to fluctuations in aggregate economic activity than those of households at the top. Inequality, then, may be countercyclical: increasing during recessions and falling during expansions.

How might these explanations apply to inequality within and between residential areas? If households of different types (i.e., in terms of age, gender, education, industry of employment) tend to reside in different neighborhoods, these mechanisms should influence overall inequality in a between-neighborhood manner. For example, if workers employed in manufacturing tend to be clustered in certain block groups, then decreasing incomes due to the decline of manufacturing should be felt primarily by households in those block groups, but not others. Similarly, if highly educated workers are geographically clustered, then rising inequality due to skill biased technological change should be mostly a between-neighborhood phenomenon as some neighborhoods experience rising incomes relative to those of others. Of course, if neighborhoods tend to be heterogeneous, we should see a city's demographic makeup, level of educational attainment, industry structure, rate of union coverage, and economic conditions influence its *within*-neighborhood inequality.

There are also a host of theories that have more explicit implications about the extent to which individuals may sort themselves residentially by income, and hence, the extent of income variation we observe either between or within neighborhoods. We consider five rather straightforward hypotheses. First, segregation may depend on the overall scale of a city. Large metropolitan areas are likely to possess greater income heterogeneity which may increase the likelihood of observing neighborhoods with extremely high or low levels of income. This feature should then translate into larger between-neighborhood differences in big cities (e.g. Jargowsky (1996)).

Second, high levels of *density* could also lead to greater income segregation if proximity increases the desire of households to surround themselves with individuals possessing similar characteristics (e.g. Cutler and Glaeser (1997)). Holding the variance of the income distribution constant, higher population density may therefore be associated with less within-neighborhood income variation, but greater between-neighborhood variation. On the other hand, density may also quantify (inversely) the extent of urban sprawl within a particular city. Some existing research has found sprawl to be directly correlated with income segregation (Yang and Jargowsky (2006)).

Third, metropolitan areas may differ with respect to how 'fractionalized' their populations are with respect to local public amenities. That is, some cities may possess relatively homogeneous populations that largely agree on what they want the local government to provide, whereas other cities may have residents that disagree sharply on this matter. Following Tiebout (1956), we should then observe differing degrees of household sorting according to those preferences across metropolitan areas. If some of those preferences tend to be correlated with income, we may see greater between-neighborhood income inequality in more politically divided metropolitan areas.

Fourth, the degree of income segregation in a city may be influenced by one particularly significant urban disamenity: crime. Cullen and Levitt (1999) show that rising crime rates within a metropolitan area tend to be associated with the out-migration of households from the central city. The effect, they find, is especially pronounced for the highly educated and those with children. Given that education is strongly correlated with income, cities with higher rates of crime may be characterized by greater income segregation.

Fifth, the extent to which cities are racially segregated may play an important role in producing income variation between and within residential areas. In fact, because black households tend to have lower incomes, part of the inequality we see across neighborhoods may be directly attributable to the extent to which blacks are geographically clustered. Cities with relatively integrated neighborhoods, on the other hand, may exhibit high levels of income variation within their residential areas.

4.2 Cross-Section Findings

To explore these hypotheses, we estimate a series of regressions of the following general form:

$$y_{mt} = \mu + \delta_t + R_m + \beta X_{mt} + \epsilon_{mt} \tag{4}$$

where y_{mt} is one of our two measures of income inequality (between and within) characterizing metropolitan area m in year t, μ is a constant, δ_t is a year dummy, R_m is a region-specific effect[14], X_{mt} is a vector of regressors, and ϵ_{mt} is a city-year-specific residual, assumed to be both heteroskedastic and correlated over time within metropolitan areas.

Following our discussion above, we specify the vector of city-year-specific covariates, X_{mt}, to include (i) the fraction of the adult population with a bachelor's degree or more, which is intended to capture the propensity of local employers to adopt skill-complementing technologies[15]; (ii) the proportions of the overall population accounted for by blacks, individuals under the age of 18, and individuals over the age of 65, as well as the fractions of single, family, and female-headed households in the total population of households; (iii) the fraction of the population that is foreign-born; (iv) the rate of union coverage among workers; (v) the share of total employment in durable and non-durable manufacturing, to capture

[14] In practice, we control for three region dummies: West, South, and Midwest.

[15] Beaudry et al. (2006) find that computer usage within a metropolitan area is highly correlated with the share of college graduates in the resident population.

the effects of trade and industrial shifts[16]; and (vi) the metropolitan area's unemployment rate, which represents the state of the local business cycle.[17]

We also include both log population and log population density to estimate the influence of overall scale and the average proximity of households to one another on the extent of income variation within and between block groups. These characteristics are derived from the USA Counties 1998 data file produced by the U.S. Census Bureau.[18] To account for the possible influence of differing degrees of Tiebout sorting, we follow Cutler et al. (1999) and add data from the 1982 Census of Governments reporting the number of local governments (county, municipal, and town or township) in each metropolitan area. This variable should capture some of the differences in the degree of political fragmentation across metropolitan areas. Finally, we include a measure of the local crime rate near each Census year (1979, 1989, 1999) given by the FBI's crime index per 1,000 residents, and an index of dissimilarity (as described, for example, by Massey and Denton (1988)) computed for black households with respect to non-black households.[19]

Summary statistics describing each of these variables in all three Census years appear

[16] Most studies of the effect of international trade, industrial shifts, and inequality focuses on manufacturing (e.g. Murphy and Welch (1992), Revenga (1992), Freeman (1995)). We also tried adding a measure of 'high-tech' manufacturing consisting of SIC 35 (Industrial Machinery), 36 (Electrical and Electronic Equipment), and 38 (Instruments), but the coefficient was never significant and did not change the remaining results noticeably.

[17] All of these quantities, with the exception of the unionization rate, are computed from the GeoLytics Census files. 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.

[18] We calculate metropolitan area density as a population-share weighted average over county-level population densities to account for the fact that some metropolitan areas may include extremely large, but sparsely populated, counties.

[19] Metropolitan area crime rates are constructed from estimates reported at the county level in the County and City Data Books: http://fisher.lib.virginia.edu/collections/stats/ccdb/. Crimes include murder, forcible rape, robbery, aggravated assault, burglary, larceny, auto theft, and arson.

in Table 3. They show a number of relatively well-known results, including the rise of the fraction of college graduates, single households, and those over 65 years of age in the population, as well as the decrease in the share of manufacturing, the rate of union coverage among workers, and the crime rate (especially during the 1990s).

Results from the estimation of (4) appear in Table 4. From them, we see a number of interesting patterns. Metropolitan areas with larger fractions of college graduates, female-headed households, and foreign-born residents all tend to have significantly greater income variation, both within and between block groups. These findings are broadly consistent with the theories of skill-biased technological adoption, the relative earnings of women, and the impact of immigration on labor markets that we sketched above. Moreover, they demonstrate that the relationship between these characteristics and overall income variation seems to operate both by influencing the degree of income variation among households within the same block group as well as that between households living in different block groups.

We do, however, see some heterogeneity in the magnitudes of these three coefficients across the two income variation measures, suggesting that there may be important differences in the extent of residential segregation of individuals by these particular characteristics. The coefficient on the college share, for example, is much larger in the between-neighborhood regressions (0.31) than the within-neighborhood regressions (0.11) suggesting that larger shares of college graduates may be associated with more extensive clustering of college graduates across residential areas. That is, as the fraction of highly educated households rises in the cross section of cities, we may observe greater concentrations of college graduates in certain neighborhoods (rather than rising numbers in all neighborhoods) leading to larger between-neighborhood income gaps. On the other hand, we see larger coefficients in the *within*-neighborhood regressions for female-headed households and foreign-born individuals, indicating that these groups may be situated in many different neighborhoods. Increasing their numbers, then, would primarily increase income heterogeneity within block groups.

There is also a positive association between the rate of unemployment and each inequality measure, although we only observe a significant relationship with between-neighborhood variation. This may indicate that economic downturns influence overall income inequality in a city primarily through a between-neighborhood channel rather than a within-neighborhood one. As described above, this would occur if workers who are especially sensitive to the business cycle (i.e. low-income, low-skill workers) tend to live in different block groups than workers who are less affected by economic fluctuations. Still, because the magnitudes of the coefficients in the between- and within-neighborhood regressions are roughly similar (respectively 0.2 and 0.14), there may not be any meaningful difference in how the unemployment rate correlates with each measure.

Unlike these four variables, many of the covariates listed in Table 4 produce coefficients across the two regressions with opposite signs, suggesting more dramatic differences in how each relates to inequality of each type. The fraction of black households in the population, for example, is positively associated with between-neighborhood income variation, but negatively associated with within-neighborhood variation. This may indicate that, in the cross section of metropolitan areas, those with larger fractions of black households are more segregated by race, leading to larger income gaps across neighborhoods. At the same time, greater racial segregation should create greater racial homogeneity *within* neighborhoods, producing lower levels of intra-neighborhood income variation. The resulting coefficients on the black dissimilarity index, which show a positive association with between-neighborhood inequality but a negative (albeit insignificant) association with within-neighborhood inequality, are consistent with this idea.

A similar pattern is discernible for both the proportion of individuals under the age of 18 and the fraction of single households in the population, possibly signifying that these groups tend to be residentially segregated from the remainder of the population. In the case of the former quantity, this result may reflect the separation of families with schoolaged children from households without children. The point estimates suggest a similar pattern for the fraction of married households, but neither of the coefficients in Table 4 is statistically important. On the other hand, the opposite is true of the population 65 years of age or older. The positive association with within-neighborhood inequality, but negative correlation with between-neighborhood inequality, suggests that older households tend to be relatively spread out residentially.

We also see that population is positively associated with between-neighborhood income differences, but negatively correlated with within-neighborhood differences. As described above, this is compatible with the idea that big cities simply possess greater heterogeneity which leads to the presence of extremely high- and low-income neighborhoods. Yet, we also see that large metropolitan areas possess less intra-neighborhood income variation, suggesting that, on the whole, big cities are characterized by greater income sorting than small cities. This latter finding may be related to the negative association we observe between population density and within-neighborhood inequality. Densities, after all, are often quite high in large metropolitan areas, which may lead to an increased demand among residents for neighbors with similar characteristics.

Crime shows a similar pair of associations, relating positively to between-neighborhood income differentials but negatively to within-neighborhood differentials. As such, there is some evidence that higher crime causes households to sort more extensively by income. Of course, these findings might also indicate that crime tends to be higher in areas of extreme poverty (e.g. Glaeser et al. (1996)). That is, the causation might run the other way: concentrations of low-income households may create conditions that foster crime.

We also find that the decline of union activity and non-durable manufacturing's share of total employment have produced greater income inequality, but in each case, the association works through differences across different block groups. Larger fractions of workers either covered by a union or employed in the production of non-durables tend to be accompanied by smaller differences between neighborhoods, not within them. Once again, this result suggests that union members and manufacturing workers may be somewhat residentially segregated from the rest of the population. The fact that non-durable manufacturing is related to inequality, but durable manufacturing is not, could indicate that workers in industries like food processing and textiles, rather than industrial machinery and instruments, have been particularly hard hit by rising international trade.

Contrary to the Tiebout sorting conjecture, we find little evidence that larger numbers of local governments (county, municipal, town or township) are associated with greater between-neighborhood income differentials. Although the coefficient is positive, it is not significant. On the other hand, we do find a significantly positive association between the number of local governments and the degree of within-neighborhood income variation. While this result may seem to contradict the Tiebout hypothesis because it suggests that greater political fragmentation is associated with less household sorting by preferences, preferences for local public goods might only be loosely related to income. That is, high- and low-income households may, in many instances, value similar amenities. It is, therefore, not completely implausible that greater sorting by preferences would be accompanied by greater within-neighborhood income heterogeneity.

4.3 Results for Changes in Inequality

Rather than looking at correlates of inequality levels, we now turn our attention to an exploration of changes in metropolitan area inequality. That is, we consider the estimation of (4) in 10-year differences:

$$\Delta y_{mt} = \Delta\delta_t + \beta\Delta X_{mt} + \Delta\epsilon_{mt} \tag{5}$$

We focus on differences for two reasons. First, the predominant interest in most existing studies of inequality has been to understand the evolution of income dispersion within the US in recent decades as opposed to the level of inequality at some point in time. Estimating

(5) provides some indication as to which types of cities experienced the largest (or smallest) increases in which type of inequality. Second, to the extent that there are unobserved, time-invariant characteristics of cities influencing the level of either within- or between-neighborhood inequality, equation (4) is misspecified. Taking differences eliminates any such metropolitan area fixed effects from the data.

The estimated coefficients appear in Table 5. On the whole, they show many of the same qualitative relationships seen from the levels estimation described in the last section. Larger fractions of college graduates, female-headed households, and foreign-born residents tend to be associated with greater inequality both within and between neighborhoods, although the foreign-born fraction's coefficient with between-neighborhood variation is not significant.

The unemployment rate again correlates positively with both measures, but only the association with between-neighborhood income inequality differs statistically from zero. This, of course, is the same pattern we observed in the levels estimation.

Larger fractions of the population accounted for by those under the age of 18, once again, tend to be accompanied by greater between-neighborhood income gaps, but smaller within-neighborhood gaps, while greater proportions of residents over the age of 65 correspond to roughly the opposite. As noted above, these results may reflect the extent to which individuals in these age categories are represented equally or unequally across block groups.

Rising population is associated with reduced levels of within-neighborhood inequality, once again suggesting that, as cities expand, their neighborhoods become increasingly homogeneous in terms of income. In this case, we do not see a significant coefficient in the between-neighborhood regression, but the point estimate is positive. As before, union activity is negatively associated with inequality between neighborhoods, and shares of employment accounted for by manufacturing are, for the most part, negatively associated with both types of residential inequality. The only significant association for manufacturing activity, however, is that for non-durables which, in this case, correlates significantly with income variation *within* neighborhoods rather than between them. This, of course, is the opposite of what we found when we performed the regressions in levels.

We also find results that differ from those in Table 4 for the fraction of black individuals in the population. Recall, in the levels estimation, we found that larger black proportions were associated with greater between-neighborhood income differentials, but smaller within-neighborhood gaps. We interpreted this pattern as suggesting that, cross sectionally, larger black proportions were associated with greater racial segregation across neighborhoods. Here, we find that, as metropolitan areas experience rising fractions of blacks in their populations, their between-neighborhood gaps drop but their within-neighborhood gaps rise, although only the former relationship is significant. This finding may indicate that, as cities have seen their black populations rise over the sample time period, they have also seen their neighborhoods become less racially segregated.[20] That is, historically, cities with larger black populations may also have been more segregated, leading to the cross-sectional results in Table 4. However, when we look at *changes* between 1980 and 2000, rising black populations may be associated with declining segregation. We do find that the black dissimilarity index remains positively associated with between-neighborhood inequality, but negatively associated with within-neighborhood inequality.

The fact that the relative magnitudes of the coefficients across the two regressions for some of our covariates do not match those from the levels regressions may have a similar explanation. For example, in levels, the college fraction showed a stronger association with between-neighborhood gaps than within-neighborhood gaps, but the opposite is true of the differences results. Cross sectionally, cities with larger fractions of college-educated households may have greater concentrations of those workers, hence, larger income gaps between neighborhoods. However, as cities have experienced increases in their college fractions in recent decades, we may have seen greater mixing of these individuals with less educated households within neighborhoods, driving up within neighborhood inequality.

[20] We find a weak negative association between the change in the black fraction and the change in black dissimilarity in our data.

The remainder of the covariates in Table 5 show insignificant correlations with both inequality measures. The crime rate does produce coefficients similar to those reported from the levels estimation: a positive association with between-neighborhood gaps and a negative association with intra-neighborhood variation. However, neither estimate is important in a statistical sense.

4.4 Results for Census Tracts

At this point, we turn our attention to the analysis of tract-level inequality. Again, while we prefer block groups to tracts due to their smaller size (and, thus, potential superiority for defining residential areas in which individuals are likely to interact with one another), many previous studies of neighborhood-level outcomes have examined tracts. In this section, we consider income inequality both within and between Census tracts in an effort to enhance the comparability of our results with those studies and to determine how robust our results are to changes in the fundamental geographic unit of analysis.

Summary statistics describing tract-based inequality appear in Table 6. Note, because the variance of a metropolitan area's log income distribution does not depend upon how we partition the population geographically, the calculation of σ^2_{mt} for each metro area m in each year t remains as before.

On average, we see the same two qualitative patterns that characterize the block group measures. In each year, the majority of overall income variation can be linked to within-tract income differentials rather than between-tract differentials. At the same time, there was a sizable increase in the extent of between-tract income inequality between 1980 and 1990. Over this decade, the between-tract share of total income inequality rose from 13 percent, on average, to 16 percent.[21]

[21] Once again, we found nearly identical results when computing the within-tract component 'directly' using tract-level data on the distribution of household income. The correlation between that measure of within-neighborhood inequality and what we report here across all metropolitan area-year observations is 0.95.

This rise, of course, is not as striking as that observed for block groups, where the between-neighborhood fraction of overall inequality increased from 13 percent to 21 percent between 1980 and 1990.[22] Given that tracts are composed of multiple block groups, this finding suggests that some of the increase in income segregation across block groups during the 1980s occurred *within* Census tracts. Some of the rise in between-block group income differentials, therefore, would not necessarily translate into an increase in between-tract differentials. As such, while the majority of the change in a typical metropolitan area's overall income inequality during the 1980s can be linked to increasing differences between block groups (67 percent), only 31 percent can be linked to rising differentials between tracts.[23]

As with the block group data, the typical metropolitan area also saw a modest decline in its between-tract inequality during the 1990s. Over this decade, changes in metropolitan area level income inequality can be attributed primarily to changes in within-tract income differentials. Among the 359 metropolitan areas in the sample, changes in within-tract income inequality accounted for roughly 86 percent of the change in total income inequality, based again on the median of the sample. This figure is similar to the fraction reported above for block groups over this same decade, 73 percent.

Just as with the block group level measures, within- and between-tract inequality both show a significantly positive, albeit somewhat modest, correlation in levels: 0.21. This figure, recall, is nearly identical to the block-group correlation, 0.24. A larger difference between the two geographies emerges when we correlate 10-year *changes* in the two measures. Among block groups, the change in within-neighborhood inequality was essentially

[22] We see a similar result looking at percentile differences. As noted previously, the 90-10 percentile gap (computed as weighted percentiles over block groups) rose between 1980 and 1990 from 0.63 to 0.87 for block groups. For tracts, the rise was much smaller: 0.63 to 0.76.

[23] Recall, these figures are calculated by taking the ratio of the change in between-neighborhood inequality to the change in overall income variance for each metropolitan area in the sample. These two statistics represent median values across the 359 metropolitan areas.

uncorrelated with the change in between-neighborhood inequality (-0.004). In the case of Census tracts, the correlation is much larger (and significantly non-zero), 0.28. Hence, as the degree of income heterogeneity increases within the tracts of a metropolitan area, the degree of income heterogeneity across those tracts also tends to rise.

Nevertheless, results from regressions of within- and between-tract inequality on the covariates considered above, which appear in Table 7, show many of the same associations seen from the analysis of block groups. Indeed, the signs of the coefficients are nearly identical across the two levels of geography. To be sure, there are some differences in terms of statistical significance. We find, for example, that the fraction of workers engaged in durable manufacturing is now significantly associated with changes in between-neighborhood income variation and that the crime rate does not correlate significantly with levels of income inequality within tracts. However, we do not believe that these differences are indicative of any meaningful disconnect between block groups and tracts.

There is, however, one potentially interesting difference between the two geographic units. The unemployment rate shows a somewhat stronger association with the degree of income variation within tracts than block groups. Although the coefficient estimates were positive in the block group regressions, neither was statistically important. Unemployment seemed to influence income inequality primarily across block groups. With tracts, however, a metropolitan area's rate of unemployment is significantly associated with greater within-tract income heterogeneity, measured either in levels or differences.

One possible explanation for these two sets of results is that, although changes in unemployment influence workers in some block groups more than others (hence, a significant association with between-block group inequality), those block groups are often located within the same tract. Hence, variation in the unemployment rate tends to be correlated with income variation within tracts, but not block groups. To the extent that this phenomenon is experienced in many different tracts throughout a metropolitan area, we should also see a smaller association between unemployment and inequality between tracts. There is some evidence that the magnitudes of the between-tract coefficients in Table 7 are smaller than the between-block group coefficients in Tables 4 and 5.

5 Concluding Discussion

This paper has offered a descriptive, empirical exploration of neighborhood income inequality across a sample of 359 metropolitan areas in the US. To recap briefly, the primary findings indicate the following. The majority of income inequality within urban areas in the country is driven by within-neighborhood differences rather than between-neighborhood differences. Depending on the year and whether we define neighborhoods as block groups or tracts, our calculations suggest that between 80 and 90 percent of a city's overall income variance is tied to the income heterogeneity within its neighborhoods.

There was, however, a considerable rise in the extent of between-neighborhood inequality during the 1980s, especially between block groups. Hence, as suggested (indirectly) by studies documenting an increase in the concentration of poverty in the US over this decade, households in the US became increasingly segregated by income at this time. Yet, this trend did not continue into the following decade. On the contrary, our estimates indicate that between-neighborhood income gaps decreased, on average, for both block groups and tracts during the 1990s.

When we examine some basic correlates of inequality, we find that several variables that existing studies have found to be associated with overall income inequality seem to have differential associations with the degree of income variation within and between neighborhoods. We believe these findings are interesting because they suggest that not all mechanisms influencing overall inequality have the same geographic effects. That is, some increase inequality through a between-neighborhood channel, others through a within-neighborhood channel, and others through both.

Based on our analysis of 10-year changes in each income variation measure, for example, we see that the business cycle and decreasing unionization influence workers in certain neighborhoods more than others. Their connection to overall inequality, therefore, lies in generating greater income segregation. Increasing numbers of foreign-born individuals in a metropolitan area's population, on the other hand, appears to do just the opposite, increasing the degree of income heterogeneity within neighborhoods, but not between them. Similarly, although rising educational attainment seems to influence both measures of inequality, its association is stronger with income variation within neighborhoods.

We believe that these findings are important because they suggest which determinants of overall inequality influence the extent of income segregation across neighborhoods and which ones do not. Those that increase residential income segregation may have a larger impact on inequality over long run time horizons because household income may have a substantial neighborhood component which transmits inequality from one generation to the next (Durlauf (1996)). Mechanisms that increase inequality among individuals residing in the same residential areas may not have the same impact.

Moreover, a large literature has argued that individuals, particularly young ones, are heavily influenced by several additional characteristics of the neighborhoods in which they reside, including education, the rate of unemployment, and the prevalence of criminal behavior.[24] Many of these characteristics, of course, are strongly correlated with income. Understanding how cities arrive at varying degrees of income heterogeneity both within and between neighborhoods, therefore, may prove useful attempting to design policies that address a number of economic and social outcomes.

[24] See, for example, Case and Katz (1991) and O'Regan and Quigley (1996).

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
	Within Share of Variance	0.87	0.06	0.68	0.99
	Between Share of Variance	0.13	0.06	0.006	0.32
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
	Within Share of Variance	0.79	0.06	0.61	0.92
	Between Share of Variance	0.21	0.06	0.08	0.39
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
	Within Share of Variance	0.8	0.06	0.64	0.95
	Between Share of Variance	0.2	0.06	0.05	0.36

Note: Statistics taken across 359 metropolitan areas.

Table 2A: Metropolitan Areas with Highest and Lowest

Overall Inequality

Top 15 Metro Areas	Average Inequality 1980-2000	Bottom 15 Metro Areas	Average Inequality 1980-2000
Bridgeport-Stamford-Norwalk, CT	0.914	Logan, UT-ID	0.513
New York-Northern New Jersey-Long Island, NY-NJ-PA	0.834	Oshkosh-Neenah, WI	0.512
College Station-Bryan, TX	0.786	Monroe, MI	0.512
Gainesville, FL	0.776	Lancaster, PA	0.511
Naples-Marco Island, FL	0.767	Janesville, WI	0.502
Los Angeles-Long Beach-Santa Ana, CA	0.766	York-Hanover, PA	0.501
Auburn-Opelika, AL	0.765	Lebanon, PA	0.494
San Francisco-Oakland-Fremont, CA	0.759	Ogden-Clearfield, UT	0.489
Laredo, TX	0.759	Holland-Grand Haven, MI	0.489
Miami-Ft. Lauderdale-Miami Beach, FL	0.759	Fond du Lac, WI	0.484
McAllen-Edinburg-Mission, TX	0.75	Sheboygan, WI	0.483
New Orleans-Metairie-Kenner, LA	0.747	Appleton, WI	0.481
Athens-Clarke County, GA	0.743	Hinesville-Fort Stewart, GA	0.479
Monroe, LA	0.742	Jacksonville, NC	0.477
Vero Beach, FL	0.737	Warner Robins, GA	0.477

Note: Inequality based on variance of log household income.

Table 2B: Metropolitan Areas with Highest and Lowest

Within-Block Group Inequality

Top 15 Metro Areas	Average Inequality 1980-2000	Bottom 15 Metro Areas	Average Inequality 1980-2000
Santa Cruz-Watsonville, CA	0.619	Springfield, OH	0.436
College Station-Bryan, TX	0.618	Sheboygan, WI	0.436
McAllen-Edinburg-Mission, TX	0.614	Fond du Lac, WI	0.434
Bridgeport-Stamford-Norwalk, CT	0.613	Muskegon-Norton Shores, MI	0.433
Morgantown, WV	0.608	Colorado Springs, CO	0.432
Lafayette, LA	0.594	Salt Lake City, UT	0.432
Athens-Clarke County, GA	0.591	Virginia Beach-Norfolk-Newport News, VA	0.431
Laredo, TX	0.591	Vallejo-Fairfield, CA	0.431
New York-Northern New Jersey-Long Island, NY-NJ-PA	0.591	Columbus, OH	0.431
Brownsville-Harlingen, TX	0.589	York-Hanover, PA	0.428
Ithaca, NY	0.588	Provo-Orem, UT	0.425
Santa Fe, NM	0.588	Fort Wayne, IN	0.423
Greenville, NC	0.587	Jacksonville, NC	0.417
Hattiesburg, MS	0.579	Warner Robins, GA	0.402
Gainesville, FL	0.578	Ogden-Clearfield, UT	0.392

Note: Within-block group variation in log household income.

Table 2C: Metropolitan Areas with Highest and Lowest

Between-Block Group Inequality

Top 15 Metro Areas	Average Inequality 1980-2000	Bottom 15 Metro Areas	Average Inequality 1980-2000
Bridgeport-Stamford-Norwalk, CT	0.301	Fond du Lac, WI	0.05
New York-Northern New Jersey-Long Island, NY-NJ-PA	0.243	Hickory-Lenoir-Morganton, NC	0.049
Naples-Marco Island, FL	0.237	Harrisonburg, VA	0.049
Memphis, TN-AR-MS	0.232	Sheboygan, WI	0.047
Tallahassee, FL	0.223	Punta Gorda, FL	0.047
Auburn-Opelika, AL	0.221	Prescott, AZ	0.046
Midland, TX	0.22	Barnstable Town, MA	0.046
New Orleans-Metairie-Kenner, LA	0.217	Kingston, NY	0.045
Waco, TX	0.209	Appleton, WI	0.044
Los Angeles-Long Beach-Santa Ana, CA	0.208	Elizabethtown, KY	0.043
Vero Beach, FL	0.203	St. George, UT	0.042
Austin-Round Rock, TX	0.199	Glen Falls, NY	0.041
Gainesville, FL	0.198	Monroe, MI	0.036
Savannah, GA	0.198	Dover, DE	0.036
Columbus, GA-AL	0.194	Hinesville-Fort Stewart, GA	0.028

Note: Between-block group variation in log household income.

Table 3: Summary Statistics - Metropolitan Area Characteristics

Year	Variable	Mean	Standard Deviation	Minimum	Maximum
1980	Fraction College	0.16	0.05	0.08	0.37
	Fraction Black	0.09	0.1	0.0002	0.43
	Fraction Under 18	0.28	0.03	0.16	0.39
	Fraction Over 65	0.11	0.03	0.02	0.34
	Fraction Single Households	0.21	0.03	0.12	0.29
	Fraction Family Households	0.75	0.04	0.61	0.86
	Fraction Female Headed Households	0.24	0.03	0.16	0.32
	Fraction Foreign Born	0.04	0.04	0.004	0.26
	Fraction Union	0.24	0.08	0.09	0.37
	Fraction Durable Manufacturing	0.17	0.11	0.01	0.73
	Fraction Non-Durable Manufacturing	0.12	0.08	0.01	0.61
	Unemployment Rate	0.07	0.02	0.02	0.15
	Population	509811.5	1241678	26065	16363540
	Density	435.4	984.7	4	14740
	Number of Governments	42.8	69.3	1	578
	Crime Rate (per 1000 residents)	53.5	16.3	10.1	99.8
	Black Dissimilarity (block group)	0.55	0.14	0.15	0.88
	Black Dissimilarity (tract)	0.54	0.15	0.15	0.88
1990	Fraction College	0.19	0.06	0.09	0.42
	Fraction Black	0.1	0.1	0.001	0.45
	Fraction Under 18	0.26	0.03	0.16	0.38
	Fraction Over 65	0.12	0.03	0.03	0.34
	Fraction Single Households	0.24	0.03	0.12	0.29
	Fraction Family Households	0.72	0.04	0.57	0.86
	Fraction Female Headed Households	0.27	0.03	0.18	0.34
	Fraction Foreign Born	0.04	0.05	0.004	0.31
	Fraction Union	0.17	0.07	0.06	0.32
	Fraction Durable Manufacturing	0.12	0.08	0.007	0.6
	Fraction Non-Durable Manufacturing	0.09	0.06	0.009	0.51
	Unemployment Rate	0.06	0.07	0.06	0.32
	Population	568813	1344409	40443	16846046
	Density	452	981.8	5.2	15161.5
	Crime Rate (per 1000 residents)	54.4	17.9	10.5	115.2
	Black Dissimilarity (block group)	0.63	0.11	0.21	0.88
	Black Dissimilarity (tract)	0.55	0.12	0.14	0.87

Table 3 Continued

Year	Variable	Mean	Standard Deviation	Minimum	Maximum
2000	Fraction College	0.22	0.07	0.1	0.52
	Fraction Black	0.1	0.11	0.001	0.49
	Fraction Under 18	0.25	0.03	0.16	0.36
	Fraction Over 65	0.13	0.03	0.04	0.35
	Fraction Single Households	0.25	0.03	0.11	0.32
	Fraction Family Households	0.69	0.05	0.53	0.86
	Fraction Female Headed Households	0.28	0.03	0.18	0.36
	Fraction Foreign Born	0.06	0.06	0.008	0.35
	Fraction Union	0.14	0.06	0.04	0.27
	Fraction Durable Manufacturing	0.11	0.07	0.008	0.45
	Fraction Non-Durable Manufacturing	0.08	0.05	0.005	0.48
	Unemployment Rate	0.06	0.02	0.03	0.14
	Population	648327.4	1495870	52457	18323002
	Density	481.1	1016	6.2	16125
	Crime Rate (per 1000 residents)	44.6	15.1	9.8	111.2
	Black Dissimilarity (block group)	0.59	0.1	0.24	0.85
	Black Dissimilarity (tract)	0.5	0.12	0.17	0.84

Note: Statistics taken across 359 metropolitan areas. Number of governments is only computed for the year 1982.

Table 4: Regression Results - Block Group Inequality Levels

Variable	*Within-Neighborhood*	*Between-Neighborhood*
Fraction College	0.11*	0.31*
	(0.06)	(0.07)
Fraction Black	-0.06*	0.042*
	(0.03)	(0.025)
Fraction Under 18	-0.15	0.29*
	(0.11)	(0.09)
Fraction Over 65	0.2*	-0.06
	(0.09)	(0.09)
Fraction Single Households	-0.24	0.28*
	(0.17)	(0.14)
Fraction Family Households	-0.03	0.03
	(0.17)	(0.18)
Fraction Female Headed Households	0.72*	0.33*
	(0.11)	(0.1)
Fraction Foreign Born	0.36*	0.2*
	(0.05)	(0.04)
Fraction Union	0.04	-0.06*
	(0.03)	(0.03)
Fraction Durable Manufacturing	-0.003	-0.002
	(0.02)	(0.02)
Fraction Non-Durable Manufacturing	-0.005	-0.035*
	(0.03)	(0.02)
Unemployment Rate	0.14	0.2*
	(0.09)	(0.07)
Log Population	-0.014*	0.007*
	(0.003)	(0.003)
Log Density	-0.007*	-0.001
	(0.003)	(0.002)
Number of Governments	0.0001*	0.00001
	(0.00003)	(0.00003)
Crime Rate	-0.0002*	0.0003*
	(0.0001)	(0.0001)
Black Dissimilarity	-0.01	0.085*
	(0.01)	(0.01)
R^2	0.54	0.72

Note: Heteroskedasticity-consistent standard errors, adjusted for correlation within metropolitan areas, are reported in parentheses. Regressions also include time effects and three region indicators. An asterisk (*) denotes significance at 10 percent or better.

Table 5: Regression Results - Changes in Block Group Inequality

Variable	*Within-Neighborhood*	*Between-Neighborhood*
Fraction College	0.39*	0.23*
	(0.09)	(0.07)
Fraction Black	0.1	-0.37*
	(0.1)	(0.1)
Fraction Under 18	-0.42*	0.25*
	(0.1)	(0.09)
Fraction Over 65	0.03	-0.26*
	(0.16)	(0.16)
Fraction Single Households	0.11	0.1
	(0.23)	(0.18)
Fraction Family Households	0.28	-0.07
	(0.21)	(0.17)
Fraction Female Headed Households	0.28*	0.64*
	(0.14)	(0.11)
Fraction Foreign Born	0.21*	0.07
	(0.12)	(0.07)
Fraction Union	0.003	-0.13*
	(0.05)	(0.05)
Fraction Durable Manufacturing	-0.042	-0.037
	(0.03)	(0.022)
Fraction Non-Durable Manufacturing	-0.17*	0.037
	(0.04)	(0.03)
Unemployment Rate	0.03	0.34*
	(0.07)	(0.06)
Log Population	-0.1*	0.02
	(0.02)	(0.02)
Log Density	0.007	-0.01
	(0.01)	(0.01)
Number of Governments	0.00001	0.000001
	(0.00001)	(0.00001)
Crime Rate	-0.0001	0.00006
	(0.0001)	(0.00007)
Black Dissimilarity	-0.06*	0.04*
	(0.02)	(0.01)
R^2	0.32	0.74

Note: Heteroskedasticity-consistent standard errors, adjusted for correlation within metropolitan areas, are reported in parentheses. Regressions also include time effects and three region indicators. An asterisk (*) denotes significance at 10 percent or better.

Table 6: Summary Statistics - Tract 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	0.38	0.64
	Between Component	0.07	0.04	0.003	0.24
	Within Share of Variance	0.87	0.06	0.68	0.995
	Between Share of Variance	0.13	0.06	0.005	0.32
1990	Variance	0.64	0.07	0.48	0.94
	Within Component	0.53	0.05	0.41	0.72
	Between Component	0.1	0.05	0.02	0.27
	Within Share of Variance	0.84	0.06	0.68	0.97
	Between Share of Variance	0.16	0.06	0.03	0.32
2000	Variance	0.65	0.08	0.48	1.05
	Within Component	0.55	0.05	0.45	0.74
	Between Component	0.09	0.04	0.01	0.34
	Within Share of Variance	0.86	0.05	0.68	0.98
	Between Share of Variance	0.14	0.05	0.02	0.32

Note: Statistics taken across 359 metropolitan areas.

Table 7: Regression Results - Tract Inequality

	Within-Neighborhood		*Between-Neighborhood*	
Variable	Levels	Differences	Levels	Differences
Fraction College	0.14*	0.44*	0.29*	0.19*
	(0.07)	(0.08)	(0.07)	(0.06)
Fraction Black	-0.08*	-0.002	0.04*	-0.25*
	(0.03)	(0.1)	(0.02)	(0.08)
Fraction Under 18	-0.08	-0.37*	0.25*	0.2*
	(0.12)	(0.1)	(0.08)	(0.08)
Fraction Over 65	0.2*	-0.1	-0.04	-0.12
	(0.09)	(0.14)	(0.08)	(0.11)
Fraction Single Households	-0.25	0.27	0.24*	-0.08
	(0.2)	(0.23)	(0.12)	(0.14)
Fraction Family Households	-0.1	0.4*	0.07	-0.2
	(0.2)	(0.21)	(0.16)	(0.14)
Fraction Female Headed Households	0.8*	0.44*	0.27*	0.49*
	(0.11)	(0.13)	(0.09)	(0.09)
Fraction Foreign Born	0.37*	0.23*	0.18*	0.06
	(0.05)	(0.13)	(0.04)	(0.06)
Fraction Union	0.03	-0.006	-0.05*	-0.12*
	(0.03)	(0.04)	(0.025)	(0.03)
Fraction Durable Manufacturing	0.006	-0.04	-0.01	-0.04*
	(0.02)	(0.03)	(0.02)	(0.02)
Fraction Non-Durable Manufacturing	-0.005	-0.15*	-0.03*	0.02
	(0.03)	(0.04)	(0.02)	(0.02)
Unemployment Rate	0.24*	0.14*	0.09	0.22*
	(0.09)	(0.07)	(0.07)	(0.05)
Log Population	-0.014*	-0.1*	0.007*	0.024*
	(0.003)	(0.02)	(0.003)	(0.014)
Log Density	-0.008*	0.007	-0.0008	-0.013
	(0.003)	(0.02)	(0.002)	(0.01)
Number of Governments	0.0001*	0.00001	0.000002	0.000005
	(0.00003)	(0.00001)	(0.00003)	(0.000008)
Crime Rate	-0.000001	-0.00008	0.0002*	0.00002
	(0.000001)	(0.00008)	(0.0001)	(0.00006)
Black Dissimilarity	-0.02	-0.08*	0.09*	0.06*
	(0.02)	(0.02)	(0.01)	(0.02)
R^2	0.66	0.54	0.67	0.58

Note: Heteroskedasticity-consistent standard errors, adjusted for correlation within metropolitan areas, are reported in parentheses. Regressions also include time effects and three region indicators. An asterisk (*) denotes significance at 10 percent or better.

References

Acemoglu, D. (1998) "Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality." *Quarterly Journal of Economics.* 113, 1055-1090.

Antonovics, K. and R. Town. (2004) "Are All the Good Men Married? Uncovering the Sources of the Marital Wage Premium." *American Economic Review Papers and Proceedings.* 94 (2), 317-321.

Abramson, A., M. Tobin, and M. VanderGoot. (1995) "The Changing Geography of of Metropolitan Opportunity: The Segregation of the Poor in Metropolitan Areas, 1970-1990." *Housing Policy Debate.* 6 (1), 45-72.

Autor, D., L. Katz, and A. Krueger. (1998) "Computing Inequality: Have Computers Changed the Labor Market?" *Quarterly Journal of Economics.* 113, 1169-1213.

Autor, D., F. Levy, and R. Murnane. (2003) "The Skill Content of Recent Technological Change: An Empirical Exploration." *Quarterly Journal of Economics.* 118, 1279-1333.

Beaudry, P., M. Doms, and E. Lewis. (2006) "Endogenous Skill Bias in Technology Adoption: City-Level Evidence from the IT Revolution." Federal Reserve Bank of San Francisco Working Paper No. 2006-24.

Bernard, A. and J.B. Jensen. (2000) "Understanding Increasing and Decreasing Wage Inequality." *The Impact of International Trade on Wages.* R. Feenstra, ed. Chicago: University of Chicago Press.

Blank, R. (1989) "Disaggregating the Effect of the Business Cycle on the Distribution of Income." *Economica.* 56, 141-163.

Borjas, G. (2003) "The Labor Demand Curve is Downward Sloping: Reexamining the Impact of Immigration on the Labor Market." *Quarterly Journal of Economics.* 118, 1335-1374.

Bound, J. and G. Johnson. (1992) "Changes in the Structure of Wages in the 1980s: An Evaluation of Alternative Explanations." *American Economic Review.* 82, 371-392.

Butcher, K. and D. Card. (1991) "Immigration and Wages: Evidence from the 1980s." *American Economic Review Papers and Proceedings.* 81 (2), 292-296.

Card, D. (1990) "The Impact of the Mariel Boatlift on the Miami Labor Market." *Industrial and Labor Relations Review.* 43, 245-257.

Case, A. and L. Katz. (1991) "The Company You Keep: The Effects of Family and Neighborhood on Disadvantaged Youths." NBER Working Paper No. 3705.

Cullen J. and S. Levitt. (1999) "Crime, Urban Flight, and the Consequences for Cities." *Review of Economics and Statistics.* 81 (2), 159-169.

Cutler, D. and E. Glaeser. (1997) "Are Ghettos Good or Bad?" *Quarterly Journal of Economics.* 112, 827-872.

Cutler, D., E. Glaeser, and J. Vigdor. (1999) "The Rise and Decline of the American Ghetto." *Journal of Political Economy.* 107, 455-506.

Deaton, A. and C. Paxson. (1997) "The Effects of Economic and Population Growth on National Saving and Inequality." *Demography.* 34, 97-114.

Duncan, O. and B. Duncan. (1955) "A Methodological Analysis of Segregation Indices." *American Sociological Review.* 20, 210-217.

Durlauf, S. (1996) "A Theory of Persistent Income Inequality." *Journal of Economic Growth.* 1, 75-93.

Durlauf, S. (2004) "Neighborhood Effects." *Handbook of Regional and Urban Economics.* Vol. 4. J. Henderson and J. Thisse eds. New York: Elsevier.

Epple, D. and H. Sieg. (1999) "Estimating Equilibrium Models of Local Jurisdictions." *Journal of Political Economy.* 107, 645-681.

Fortin, N. and T. Lemieux. (1997) "Institutional Changes and Rising Wage Inequality: Is There a Linkage?" *Journal of Economic Perspectives.* 11, 75-96.

Freeman, R. (1995) "Are Your Wages Set in Beijing?" *Journal of Economic Perspectives.* 9, 15-32.

Glaeser, E., B. Sacerdote, and J. Scheinkman. (1996) "Crime and Social Interactions." *Quarterly Journal of Economics.* 111 (2), 507-548.

Hardman, A. and Y. Ioannides. (2004) "Neighbors' Income Distribution: Economic Segregation and Mixing in US Urban Neighborhoods." *Journal of Housing Economics.* 13(4), 368-382.

Hirsch, B., D. Macpherson, and W. Vroman. (2001) "Estimates of Union Density by State." *Monthly Labor Review.* 124 (7), 51-55.

Ioannides, Y. (2004) "Neighborhood Income Distributions." *Journal of Urban Economics.* 56, 435-457.

Ioannides, Y. and T. Seslen. (2002) "Neighborhood Wealth Distributions." *Economics Letters.* 76, 357-367.

Jakubs, J. (1986) "'Recent Racial Segregation in the U.S. SMSAs." *Urban Geography.* 7 (2), 146-163.

Jargowsky, P. (1996) "Take the Money and Run: Economic Segregation in U.S. Metropolitan Areas." *American Sociological Review.* 61 (6), 984-998.

Johnson, N. and S. Kotz. (1970) *Continuous Univariate Distributions.* Boston: Houghton Mifflin.

Juhn, C., K. Murphy, and B. Pierce. (1993) "Wage Inequality and the Rise in Returns to Skill." *Journal of Political Economy.* 101, 410-442.

Lee, D. (1999) "Wage Inequality in the United States During the 1980s: Rising Dispersion or Falling Minimum Wage?" *Quarterly Journal of Economics.* 114, 977-1023.

Kasarda, J. (1993) "Inner-City Concentrated Poverty and Neighborhood Distress: 1970-1990." *Housing Policy Debate.* 4 (3), 253-302.

Kim, J. and P. Jargowsky. (2005) "The Gini Coefficient and Segregation on a Continuous Variable." Working Paper, National Poverty Center, University of Michigan.

Massey, D. and N. Denton. (1988) "The Dimensions of Residential Segregation." *Social Forces*. 67 (2), 281-315.

Massey, D. and M. Eggers. (1990) "The Ecology of Inequality: Minorities and the Concentration of Poverty, 1970-1980." *American Journal of Sociology*. 95 (5), 1153-1188.

Madden, J. (2000) *Changes in Income Inequality within US Metropolitan Areas*. Kalamazoo, MI: Upjohn Institute for Employment Research.

Mayer, C. (1996) "Does Location Matter?" *New England Economic Review*. May/June. 26-40.

Mayer, S. (2001) "How the Growth in Income Inequality Increased Economic Segregation." Working Paper, Harris School, University of Chicago.

Murphy, K. and F. Welch. (1992) "The Structure of Wages." *Quarterly Journal of Economics*. 107, 285-326.

O'Regan, K. and J. Quigley. (1996) "Spatial Effects upon Employment Outcomes: The Case of New Jersey Teenagers." *New England Economic Review*. May/June. 41-58.

Pack, J. (2002) *Growth and Convergence in Metropolitan America*. Washington, DC: Brookings Institution Press.

Revenga, A. (1992) "Exporting Jobs? The Impact of Import Competition on Employment and Wages in U.S. Manufacturing." *Quarterly Journal of Economics*. 107, 255-284.

Taeuber, K. and A. Taeuber. (1965) *Negroes in Cities: Residential Segregation and Neighborhood Change*. Chicago: Aldine.

Tiebout, C. (1956) "A Pure Theory of Local Expenditures." *Journal of Political Economy*. 64 (5), 416-424.

Topel, R. (1997) "Factor Proportions and Relative Wages: The Supply-Side Determinants of Wage Inequality." *Journal of Economic Perspectives*. 11, 55-74.

Wilson, W. (1997) *When Work Disappears: The World of the New Urban Poor*. New York: Vintage.

Yang, R. and P. Jargowsky. (2006) "Suburban Development and Economic Segregation in the 1990s." *Journal of Urban Affairs*. 28 (3), 253-273.