The Rising Residential Concentration of Joblessness in Urban America
1980 to 2000

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Summary

Metropolitan areas in the United States have long been characterized by sharp differences across their residential areas. Some neighborhoods, for example, are populated by individuals with relatively high incomes, stocks of wealth and levels of education, while others tend to have residents who are much less well-off. A similar result holds for unemployment: Some neighborhoods tend to have high rates of employment among their residents whereas others are rife with joblessness. While basic differences of this sort are widely known, little attention has been paid to their trends over time. This report focuses on the trends in neighborhood-level unemployment across more than 166,000 Census block groups within 361 U.S. metropolitan areas. The findings indicate the following:

(1) Neighborhoods became increasingly polarized into high- and low-unemployment areas between 1980 and 2000. Unemployment rates tended to fall in neighborhoods that already had low rates of unemployment in 1980, while they tended to rise in neighborhoods that had relatively high rates of unemployment in 1980. Unemployed workers, therefore, became increasingly concentrated in relatively few residential areas in the last two decades of the 20th century.

(2) Consistent with what one would expect, the rate of joblessness in a neighborhood is strongly associated with the education and income levels of its residents. Higher incomes and levels of schooling are associated with lower unemployment. Unemployment rates also tend to be lower in neighborhoods with fewer workers employed in manufacturing, smaller fractions of nonwhite households and larger numbers of workers with relatively short commute times.

(3) Three theories for the rise in unemployment concentration are considered. First, urban decentralization (i.e., sprawl) may have moved jobs away from city centers and left clusters of unemployed workers behind. Second, the decline of certain industrial sectors (e.g., manufacturing) and the rise of others (e.g., financial services) may have affected workers living in different neighborhoods in different ways, leading unemployment to rise in some areas but fall in others. Third, the extent to which individuals with high levels of income and education (i.e., those who tend to have the lowest incidence of unemployment) are residentially segregated from the remainder of the population may have increased. The statistical results show the greatest support for this last theory. On average, college graduates became increasingly segregated (residentially) from those without college degrees between 1980 and 2000. Differences in the average incomes of households living in different neighborhoods also rose over this period.

(4) Four metropolitan areas within the Eighth Federal Reserve District—Little Rock, Louisville, Memphis and St. Louis—all saw increases in unemployment concentration between 1980 and 2000, although the rise was not as pronounced in Louisville as in the other three. In all four metro areas, the residential segregation of college graduates and the degree of income variation across neighborhoods rose over this same period.

(5) These findings may have important implications for policies that attempt to address unemployment. In particular, because the concentration of unemployment within certain neighborhoods may further complicate the job search process, efforts to help workers find and maintain employment should incorporate policies that influence the residential distribution of unemployment. Such policies may include efforts to bring economic activity closer to areas with high unemployment, encouraging households with high levels of income and education to reside in less homogeneous areas or assisting workers residing in high-unemployment areas to relocate to different neighborhoods.

Introduction

The unemployment rate is one of the most basic indicators used to gauge the state of the economy. High rates, of course, tend to occur in recessionary periods when levels of economic activity decline, while lower rates tend to prevail in times of expansion when employers typically increase the size of their payrolls. Over time, as the economy fluctuates between periods of expansion and recession, we see corresponding changes in the unemployment rate.

While this temporal variation in unemployment is widely known, there is also a fair amount of variation geographically. At any point in time, unemployment can differ substantially across states, cities and counties as a result of differences in industrial compositions, labor market demographics and region-specific shocks.

Geographic variation even extends down to extremely small areas: Census tracts and block groups (i.e., neighborhoods).[1] Therefore, within the same metropolitan area, some neighborhoods have a much higher incidence of unemployment than others.

To be sure, residential areas in the United States have long exhibited a tremendous amount of heterogeneity with respect to the characteristics of the households that inhabit them. Some neighborhoods, quite simply, tend to be populated by individuals with high levels of income and wealth, whereas others are inhabited by relatively poor households. It is, therefore, not at all surprising that, within any local labor market, there would be neighborhoods with high levels of unemployment and those with low levels.

What is, however, particularly interesting about the extent to which individuals "sort" themselves by characteristics, such as the incidence of unemployment, concerns the potential implications for various labor market outcomes. In particular, a large literature examining social interactions has argued that the characteristics of an individual's residential area greatly influence one's economic outcomes.

Economists Anne Case and Lawrence Katz (1991), for instance, have found evidence of strong peer effects among a variety of behaviors—including schooling, criminal activity, drug and alcohol use, and employment status—within a sample of residential areas in Boston. As these types of behaviors become more prevalent in a community, the propensity for young residents to engage in similar activity rises.

A study by Giorgio Topa (2001), an economist at the Federal Reserve Bank of New York, finds evidence of local "spillovers" in unemployment across Census tracts in Chicago. High levels of unemployment within a neighborhood tend to have a negative influence on the employment prospects of individuals residing within or near that neighborhood. This result may be related to the findings of the sociologist Mark Granovetter (1995), who found that workers in the United States locate jobs primarily through personal contacts, many of whom live nearby.

The prominent scholar William Julius Wilson (1987) has identified these types of neighborhood-level influences as forming the basis of the rise in inner city poverty in the United States in recent decades. As successful workers have gradually left inner cities, Wilson argues, those who remain are surrounded by rising levels of poverty and joblessness, which makes it increasingly less likely that the residents of these areas will find work.

Understanding the extent to which individuals are segregated, therefore, is clearly an important topic. However, while existing research has looked at residential segregation based on race (e.g., Cutler et al, 1999) and income (e.g., Wheeler, 2006), relatively little work has studied the segregation of the unemployed from the employed.[2]

This study attempts to do so by examining the distribution of unemployment across metropolitan area-level neighborhoods, defined by Census block groups, over the years 1980, 1990 and 2000. Block groups, once again, are relatively small geographic areas, covering roughly 0.33 square miles and containing approximately 500 households, on average. After documenting the trends in the extent of unemployment concentration within more than 166,000 block groups across 361 metropolitan areas, three possible explanations are discussed and evaluated.

Data and Measurement Issues

The data are taken from the decennial U.S. Census of Population as compiled by GeoLytics (www.geolytics.com). These files identify a variety of characteristics of households residing in a host of geographic units, including counties, tracts and block groups, throughout the entire country. The primary advantage of the GeoLytics files is the consistency of the spatial units for which the data are identified. GeoLytics maintains a constant set of definitions in computing aggregate statistics for block groups, tracts, counties and all other geographic entities. As a result, the statistics reported for each spatial unit are directly comparable from one year to the next.

From these data, a number of variables were created at the metropolitan-area level, including population demographics, density (i.e., residents per square mile) and industrial composition. A rate of union coverage for each metropolitan area was constructed using state-level rates reported by Hirsch et al (2001).[3] These quantities are intended to help identify characteristics associated with changes in the geographic distribution of unemployment within a city.[4]

The primary object of interest—the degree to which unemployment is spatially concentrated—is measured in two fundamental ways. First, the differences between three percentiles (90th, 50th and 10th) of the distribution of block group-level unemployment rates was computed.[5] Higher values of these three differentials (90-10, 90-50, 50-10) indicate greater disparity (i.e., higher concentration) among neighborhood-level unemployment rates.

Second, an index of dissimilarity was calculated. This measures the degree to which the members of a particular group (in this case, unemployed individuals) are unevenly distributed throughout a city's neighborhoods. This index is computed as follows: where $unemp_i$ is the number of unemployed individuals in neighborhood i, $unemp_{total}$ is the number of unemployed individuals in the metropolitan area, emp_i is the number of employed individuals in neighborhood i, emp_{total} is the number of employed individuals in the metropolitan area, and N is the total number of neighborhoods in the metropolitan area.

As described by Cutler et al (1999), the index of dissimilarity ranges between 0 (least concentrated) and 1 (most concentrated) and is commonly interpreted as the fraction of unemployed individuals that would need to move (i.e., change neighborhood of residence) for the unemployed to be uniformly distributed across a city's neighborhoods. This particular metric has been widely used in the literature studying trends in racial segregation, but it can be applied readily to the analysis of segregation based on any binary indicator, (i.e., a variable that takes on one of two possible values, such as whether an individual belongs to a group or not).

For this study, *neighborhoods* are defined as block groups, which are the smallest geography for which detailed Census data are publicly available. Block groups are quite small. In the year 2000, they averaged approximately 500 households and covered roughly a third of a square mile. Households within the same block group, then, can reasonably be expected to have some sort of interaction with one another (e.g., passing on the street). Conceptually, this feature of block groups matches well with the theoretical literature on neighborhood effects (e.g., Benabou, 1993), which treats neighborhoods as areas over which economic agents come into contact with one another.

$$(1) \quad Dissimilarity = \frac{1}{2}\sum_{i=1}^{N}\left|\frac{unemp_i}{unemp_{total}} - \frac{emp_i}{emp_{total}}\right|$$

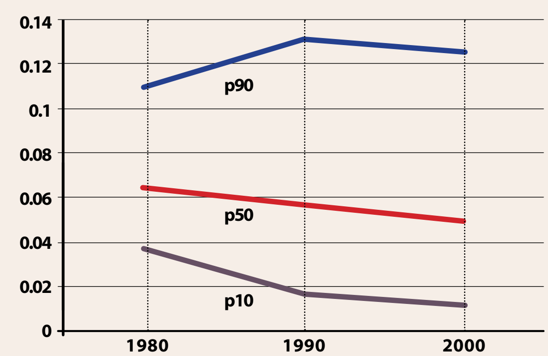
The Trend in Unemployment Concentration

Between 1980 and 2000, the unemployed became increasingly concentrated in relatively few residential areas. For example, in 1980, the median unemployed worker lived in a block group with an unemployment rate of 7.5 percent (i.e., the unemployment rate within a worker's own block group of residence was 7.5 percent or greater for at least 50 percent of all unemployed workers).[6] Two decades later, this worker lived in a block group with an unemployment rate of 7.9 percent. This trend is particularly striking in light of the fact that the average metropolitan area unemployment rate declined from 6.9 percent to 5.9 percent over this period.

Rising residential concentration of the unemployed is also apparent from the index of dissimilarity and the percentile differentials. Summary statistics describing each of these quantities over the 361 metropolitan areas in the sample appear in Table 1.[7] On average, the dissimilarity index increased from 0.18 in 1980 to 0.31 in 2000. Again, interpreting this index as the fraction of unemployed workers that would need to move for the unemployed to be uniformly distributed in a metropolitan area, these results reveal an enormous increase in the concentration of unemployment. An additional 13 percent of all unemployed workers would have needed to move in 2000 to equalize unemployment across all neighborhoods.

The percentile differences reveal a qualitatively similar pattern. In 1980, the average difference between the neighborhood at the 90th percentile of the unemployment distribution and the neighborhood at the 10th percentile was 7.3 percentage points (e.g., a difference between an unemployment rate of 8.3 percent and one of 1 percent). Two decades later, the difference was 11.2 percentage points. Based on the 90-50 and 50-10 differences, it is clear that this increase occurred at both the top and bottom of the neighborhood unemployment distribution, although the majority of the increase in the 90-10 gap was associated with an increase of the 90th percentile relative to the median. The average 90-50 gap increased by three percentage points between 1980 and 2000, whereas the mean 50-10 gap increased by one percentage point.

Figure 1: Neighborhood Unemployment Percentiles



These trends are displayed graphically in Figure 1, which plots the average values of the 90th, 50th and 10th percentiles between 1980 and 2000. Much of the widening of neighborhood unemployment distributions within the urban areas of the United States took place between 1980 and 1990, when the average 90th percentile rose while the 50th and 10th percentiles decreased. Between 1990 and 2000, all three percentiles actually decreased by similar amounts, leaving the three differentials mostly unchanged.[8]

Table 1. Summary Statistics: Unemployment Concentration

Year	Mean	Mean	Standard Deviation	Minimum	Maximum
1980	dissimilarity	0.18	0.04	0.047	0.3
	90-10 difference	0.073	0.029	0.007	0.18
	90-50 difference	0.046	0.022	0.001	0.126
	50-10 difference	0.027	0.011	0.005	0.082
	90th percentile	0.11	0.038	0.03	0.252
	50th percentile	0.064	0.022	0.019	0.147
	10th percentile	0.037	0.017	0	0.106
1990	dissimilarity	0.27	0.04	0.16	0.38
	90-10 difference	0.113	0.039	0.051	0.268
	90-50 difference	0.074	0.03	0.025	0.211
	50-10 difference	0.039	0.013	0.016	0.097
	90th percentile	0.131	0.043	0.051	0.303
	50th percentile	0.057	0.018	0.026	0.137
	10th percentile	0.018	0.009	0	0.052
2000	dissimilarity	0.31	0.05	0.15	0.5
	90-10 difference	0.112	0.037	0.049	0.271
	90-50 difference	0.076	0.029	0.031	0.206
	50-10 difference	0.037	0.012	0.015	0.092
	90th percentile	0.125	0.042	0.054	0.3
	50th percentile	0.049	0.018	0.022	0.132
	10th percentile	0.013	0.009	0	0.047

Characteristics of High- and Low-Unemployment Neighborhoods

To provide some idea about what neighborhoods with either high or low levels of unemployment look like, this section describes how a number of basic household characteristics of a block group vary with its rate of joblessness. Table 2 reports a series of statistical associations between the rate of unemployment among the households of a block group and various features of that block group. Differences across time (e.g., the general level of unemployment may be fundamentally different in 1980 than 1990) and metropolitan areas (e.g., the level of unemployment may be fundamentally different in St. Louis and New York) were taken into account.[9] This latter point is especially important because it implies that the results are based upon the comparison of neighborhoods within the *same* metropolitan area.

Most of the associations turn out to be quite reasonable, at least in the sense that they are consistent with what one would expect to see. Neighborhoods with higher average household incomes, for example, tend to see lower unemployment rates, which can be interpreted in at least two ways. First, employed households tend to have more income than unemployed households because only the former receive earnings from a job. Second, individuals with high incomes tend to be relatively successful in the labor market because they are highly skilled. These types of individuals have a much lower incidence of unemployment.

Among the demographic quantities, we see generally that larger fractions of foreign-born, female, nonwhite and nonmarried households tend to be associated with higher rates of unemployment. Such results are consistent with the finding that individuals belonging to these groups tend to have less successful labor market outcomes, particularly with respect to earnings. Here, we also see that the incidence of unemployment tends to be higher where these types of individuals are more heavily represented.

Table 2 also shows the associations between unemployment and travel time to work. Each one characterizes the relationship between a block group's unemployment rate and the fraction of its employed households that have commute times belonging to a specific category: less than five minutes, five to nine minutes, 10 to 14 minutes, 15 to 19 minutes, 20 to 29 minutes, 30 to 44 minutes, 45 to 59 minutes and an hour or more. The resulting associations seem to imply that, as the fraction of households with longer commutes rises, the incidence of unemployment increases. To be sure, the pattern is not perfect. Larger fractions of households with the shortest of all commute times, zero to five minutes, after all, tend to be accompanied by *higher* unemployment rates. However, on the whole, the estimates suggest that longer commutes are associated with more joblessness.

The five educational attainment characteristics that quantify the proportions of adult residents (at least 25 years of age) within each neighborhood who have (1) no high school, (2) some high school, (3) a high school degree only, (4) some college or an associate's degree or (5) a bachelor's degree or more, also produce very intuitive results.

Higher proportions of individuals with relatively low levels of schooling (no more than a high school diploma) tend to be associated with higher rates of unemployment, whereas neighborhoods with larger proportions of college-educated residents tend to exhibit much lower rates of unemployment. As demonstrated by the mean household income result discussed previously, skilled (here, highly educated) individuals tend to have more successful labor market outcomes.

The estimated associations from the four age distribution variables—the fractions of each neighborhood's population under 25 years of age, between 25 and 44, between 45 and 64, and 65 or older—indicate that older workers tend to experience lower rates of unemployment, which is a straightforward finding. After all, individuals between 25 and 64, the so-called prime working years, are especially likely to have a job.

Finally, there is some evidence that a neighborhood's rate of unemployment is significantly tied to the industries in which its residents are employed. In particular, larger fractions of workers in construction, wholesale trade, finance-insurance-real

Table 2. Correlates of Neighborhood Unemployment Rates

Characteristic	Coefficient Estimate	Standard Error
mean household income ($1,000s)	–0.0009*	0.000007
% foreign-born	0.07*	0.001
% female	0.04*	0.005
% nonwhite	0.12*	0.0004
% married	–0.18*	0.001
% travel time to work: 0 to 5 minutes	0.016*	0.004
% travel time to work: 5 to 9 minutes	–0.03*	0.002
% travel time to work: 10 to 14 minutes	–0.03*	0.002
% travel time to work: 15 to 19 minutes	0.006*	0.002
% travel time to work: 20 to 29 minutes	–0.06*	0.001
% travel time to work: 30 to 44 minutes	0.02*	0.001
% travel time to work: 45 to 59 minutes	0.05*	0.002
% travel time to work: 60 minutes or more	0.11*	0.002
% no high school	0.24*	0.001
% some high school	0.37*	0.002
% high school graduate	0.01*	0.001
% some college	–0.22*	0.002
% college graduate or higher	–0.14*	0.0006
% under 25 years of age	0.2*	0.002
% 25 to 44 years of age	–0.12*	0.002
% 45 to 64 years of age	–0.21*	0.002
% over 64 years of age	–0.04*	0.001
% manufacturing	0.04*	0.001
% construction	–0.02*	0.003
% wholesale trade	–0.23*	0.007
% retail trade	–0.002	0.003
% finance-insurance-real estate	–0.29*	0.004
% public administration	0.03*	0.004
% education services	–0.08*	0.003
% health services	0.09*	0.003

Note: Coefficient estimates represent statistical associations with the unemployment rate. All regressions account for time effects and metropolitan area fixed effects. Standard errors are adjusted to account for heteroskedasticity. An asterisk (*) denotes statistical significance at conventional levels.

estate and education services tend to have lower rates of unemployment. Given that workers in finance-insurance-real estate and education services tend to be relatively well-educated, this result is quite sensible. The results for construction and wholesale trade, on the other hand, may simply be related to the strong growth of these industries between 1980 and 2000. The fact that, over this same period, manufacturing in the United States saw a substantial decline in its level of employment likely explains the positive association between the share of individuals employed in this sector and a neighborhood's rate of unemployment. There is also a positive association between unemployment and the shares of employment in public administration and health services, but there is no obvious explanation for these results.

Patterns within Four Metro Areas of the Eighth Federal Reserve District

Although both the trend in unemployment concentration and the basic correlates of neighborhood-level unemployment just described are based on the analysis of data from more than 166,000 block groups in 361 metropolitan areas, many of the same results hold for four metropolitan areas within the Eighth Federal Reserve District: Little Rock, Louisville, Memphis and St. Louis. Consider first the overall trends in the geographic concentration of unemployment in each metro area.

Beginning with Little Rock, the unemployment dissimilarity index rose from 0.21 in 1980 to 0.27 in 1990 and 0.36 by 2000. Recall, these figures can be interpreted as the proportion of all unemployed workers that would have to move for unemployment to be uniformly distributed across a metropolitan area's neighborhoods. Larger values, therefore, imply greater concentration. There is also a growing gap when we look at Little Rock's percentile differences. The difference between the neighborhood at the 90th percentile of the unemployment scale and the neighborhood at the 10th percentile was 7.5 percentage points in 1980 (e.g., a difference between an unemployment rate of 8.5 percent in one neighborhood and 1 percent in the other). By 2000, this figure stood at 12 percentage points.

Louisville, by contrast, did not see as striking a rise in its degree of unemployment concentration although, on average, unemployment did become more unevenly distributed between 1980 and 2000. The index of dissimilarity, for example, increased from 0.208 in 1980 to 0.324 in 2000. However, there was not a substantial change in the difference between the 90th and 10th percentiles of the neighborhood unemployment distribution. This figure only changed from 10.3 percentage points in 1980 to 10.5 percentage points in 2000. While this latter result may seem to contradict the rise in the dissimilarity index, it is important to note that the percentile difference is based on the difference between the unemployment rates in two neighborhoods. None of the remaining neighborhoods in the metro area enter directly into its calculation. All neighborhoods, however, contribute to the computation of the dissimilarity index. Therefore, neighborhoods closer to the center of the distribution (say, near the 50th percentile) may have become increasingly dissimilar, thereby increasing the dissimilarity index, while those far away from the center (e.g., the 90th and 10th percentiles) may have changed little. This likely explains Louisville's experience over these two decades.

Memphis' experience was much closer to Little Rock's, as it saw both its unemployment dissimilarity and 90-10 percentile gap increase over this period. In 1980, Memphis had a dissimilarity value of 0.278 and a 90-10 difference of 13 percentage points. Two decades later, these figures had grown to, respectively, 0.387 and 17.1 percentage points.

St. Louis also experienced an increase in both measures of unemployment concentration. The dissimilarity index increased from 0.221 to 0.363 between 1980 and 2000. The 90-10 percentile difference rose from 11.4 percentage points to 15.2 percentage points.

Again, what makes these trends particularly striking is that, over this same period, metropolitan area-level unemployment rates decreased. Little Rock's unemployment rate decreased from 5.4 percent to 5.2 percent between 1980 and 2000. In Louisville, the unemployment rate dropped from 8 percent to 4.6 percent, while in Memphis, it fell from 7.9 percent to 6.5 percent.

Table 3A. Characteristics of Little Rock Block Groups by Unemployment Rate

Characteristic	Lowest 25%	25% to 50%	50% to 75%	Highest 25%
unemployment rate	0.017	0.037	0.058	0.11
mean household income (dollars)	57,539.9	45,802.3	36,632.8	30,508
% foreign-born	0.02	0.018	0.014	0.017
% female	0.52	0.52	0.51	0.52
% nonwhite	0.1	0.15	0.18	0.45
% married	0.64	0.63	0.61	0.53
% travel time to work: 0 to 5 minutes	0.03	0.03	0.04	0.037
% travel time to work: 5 to 9 minutes	0.12	0.11	0.12	0.13
% travel time to work: 10 to 14 minutes	0.15	0.156	0.145	0.17
% travel time to work: 15 to 19 minutes	0.19	0.19	0.17	0.2
% travel time to work: 20 to 29 minutes	0.25	0.24	0.21	0.2
% travel time to work: 30 to 44 minutes	0.166	0.18	0.21	0.17
% travel time to work: 45 to 59 minutes	0.05	0.05	0.07	0.05
% travel time to work: 60 minutes or more	0.03	0.03	0.04	0.04
% no high school	0.05	0.07	0.13	0.15
% some high school	0.09	0.12	0.16	0.2
% high school graduate	0.285	0.32	0.37	0.33
% some college	0.26	0.26	0.21	0.21
% college graduate or higher	0.31	0.23	0.13	0.11
% under 25 years of age	0.34	0.37	0.4	0.43
% 25 to 44 years of age	0.33	0.33	0.31	0.28
% 45 to 64 years of age	0.22	0.2	0.19	0.17
% over 64 years of age	0.11	0.1	0.1	0.12
% manufacturing	0.1	0.14	0.18	0.18
% construction	0.059	0.06	0.07	0.06
% wholesale trade	0.048	0.05	0.05	0.037
% retail trade	0.14	0.15	0.16	0.16
% finance-insurance-real estate	0.08	0.07	0.05	0.045
% public administration	0.064	0.063	0.05	0.055
% education services	0.081	0.074	0.07	0.07
% health services	0.126	0.116	0.1	0.12

Note: Average characteristics for neighborhoods in each of four quartiles of the neighborhood unemployment distribution.

St. Louis saw its unemployment rate decline from 7.8 percent to 5.5 percent. Despite the fact that, on the whole, each of these cities saw its labor market conditions strengthen between 1980 and 2000, unemployment clearly remained problematic for individuals in certain neighborhoods.

Summaries of the characteristics considered in the last section appear in Tables 3A-3D for these four metropolitan areas. To provide a sense of how these neighborhood features vary with the

Table 3B. Characteristics of Louisville Block Groups by Unemployment Rate

Characteristic	Lowest 25%	25% to 50%	50% to 75%	Highest 25%
unemployment rate	0.018	0.043	0.069	0.136
mean household income (dollars)	62,619.7	48,804.9	39,408.6	29,813
% foreign-born	0.024	0.017	0.016	0.012
% female	0.51	0.52	0.51	0.52
% nonwhite	0.07	0.07	0.11	0.32
% married	0.62	0.61	0.6	0.52
% travel time to work: 0 to 5 minutes	0.026	0.025	0.028	0.028
% travel time to work: 5 to 9 minutes	0.09	0.1	0.1	0.098
% travel time to work: 10 to 14 minutes	0.15	0.14	0.14	0.15
% travel time to work: 15 to 19 minutes	0.18	0.18	0.166	0.18
% travel time to work: 20 to 29 minutes	0.28	0.27	0.25	0.23
% travel time to work: 30 to 44 minutes	0.19	0.2	0.22	0.2
% travel time to work: 45 to 59 minutes	0.04	0.05	0.06	0.062
% travel time to work: 60 minutes or more	0.04	0.04	0.04	0.055
% no high school	0.055	0.09	0.15	0.2
% some high school	0.1	0.13	0.17	0.23
% high school graduate	0.29	0.34	0.38	0.34
% some college	0.28	0.24	0.185	0.15
% college graduate or higher	0.28	0.19	0.11	0.07
% under 25 years of age	0.32	0.34	0.38	0.42
% 25 to 44 years of age	0.32	0.32	0.31	0.29
% 45 to 64 years of age	0.23	0.22	0.2	0.18
% over 64 years of age	0.13	0.12	0.11	0.11
% manufacturing	0.17	0.19	0.24	0.24
% construction	0.06	0.06	0.06	0.06
% wholesale trade	0.044	0.045	0.04	0.036
% retail trade	0.133	0.15	0.15	0.15
% finance-insurance-real estate	0.08	0.07	0.06	0.049
% public administration	0.04	0.042	0.046	0.05
% education services	0.08	0.08	0.067	0.066
% health services	0.11	0.1	0.08	0.09

Note: Average characteristics for neighborhoods in each of four quartiles of the neighborhood unemployment distribution.

rate of unemployment, the tables provide the average value for each quantity within four quartiles. That is, the first column, labeled "Lowest 25%," represents block groups in the bottom 25 percent of all unemployment rates (those neighborhoods with the lowest rates of joblessness), whereas the last column, labeled "Highest 25%," summarizes characteristics of block groups with the highest unemployment rates. In between, the columns describe the average features of neighborhoods fall-

Table 3C. Characteristics of Memphis Block Groups by Unemployment Rate

Characteristic	Lowest 25%	25% to 50%	50% to 75%	Highest 25%
unemployment rate	0.018	0.045	0.084	0.181
mean household income (dollars)	68,445.7	47,084.4	36,170.9	25,563.9
% foreign-born	0.029	0.022	0.017	0.01
% female	0.51	0.52	0.52	0.53
% nonwhite	0.16	0.27	0.5	0.84
% married	0.65	0.6	0.55	0.43
% travel time to work: 0 to 5 minutes	0.02	0.025	0.02	0.026
% travel time to work: 5 to 9 minutes	0.09	0.095	0.09	0.09
% travel time to work: 10 to 14 minutes	0.135	0.13	0.13	0.13
% travel time to work: 15 to 19 minutes	0.17	0.17	0.18	0.18
% travel time to work: 20 to 29 minutes	0.27	0.26	0.24	0.23
% travel time to work: 30 to 44 minutes	0.23	0.22	0.22	0.22
% travel time to work: 45 to 59 minutes	0.05	0.06	0.06	0.06
% travel time to work: 60 minutes or more	0.03	0.04	0.05	0.064
% no high school	0.04	0.09	0.15	0.24
% some high school	0.08	0.13	0.19	0.25
% high school graduate	0.25	0.33	0.34	0.28
% some college	0.31	0.26	0.21	0.16
% college graduate or higher	0.33	0.18	0.11	0.07
% under 25 years of age	0.35	0.38	0.42	0.47
% 25 to 44 years of age	0.34	0.33	0.3	0.26
% 45 to 64 years of age	0.21	0.2	0.18	0.16
% over 64 years of age	0.1	0.09	0.1	0.11
% manufacturing	0.12	0.14	0.17	0.16
% construction	0.05	0.06	0.06	0.05
% wholesale trade	0.06	0.06	0.05	0.043
% retail trade	0.14	0.15	0.15	0.15
% finance-insurance-real estate	0.08	0.06	0.044	0.03
% public administration	0.05	0.05	0.05	0.05
% education services	0.08	0.07	0.07	0.08
% health services	0.1	0.09	0.09	0.1

Note: Average characteristics for neighborhoods in each of four quartiles of the neighborhood unemployment distribution.

ing between the 25th and 50th percentiles and the 50th and 75th percentiles.

Each table begins by reporting the average unemployment rate within each quartile to provide some idea about how much it varies from one quartile to the next. Across all four metropolitan areas, the unemployment rate among the lowest 25 percent of neighborhoods is roughly similar: somewhere in the vicinity of 1.7 percent to 1.9 percent. This figure is very close to what economists have labeled

Table 3D: Characteristics of St. Louis Block Groups by Unemployment Rate

Characteristic	Lowest 25%	25% to 50%	50% to 75%	Highest 25%
unemployment rate	0.019	0.043	0.068	0.152
mean household income (dollars)	68,365.7	53,096.4	43,287.2	32,643.9
% foreign-born	0.031	0.027	0.02	0.015
% female	0.52	0.52	0.52	0.53
% nonwhite	0.076	0.1	0.13	0.47
% married	0.63	0.6	0.59	0.49
% travel time to work: 0 to 5 minutes	0.025	0.027	0.033	0.03
% travel time to work: 5 to 9 minutes	0.1	0.1	0.11	0.1
% travel time to work: 10 to 14 minutes	0.13	0.13	0.14	0.13
% travel time to work: 15 to 19 minutes	0.15	0.15	0.16	0.16
% travel time to work: 20 to 29 minutes	0.24	0.23	0.22	0.22
% travel time to work: 30 to 44 minutes	0.24	0.23	0.22	0.21
% travel time to work: 45 to 59 minutes	0.07	0.08	0.08	0.076
% travel time to work: 60 minutes or more	0.04	0.044	0.054	0.074
% no high school	0.056	0.1	0.15	0.2
% some high school	0.08	0.11	0.14	0.21
% high school graduate	0.26	0.32	0.36	0.32
% some college	0.28	0.25	0.21	0.18
% college graduate or higher	0.32	0.23	0.15	0.09
% under 25 years of age	0.33	0.35	0.37	0.42
% 25 to 44 years of age	0.31	0.31	0.3	0.27
% 45 to 64 years of age	0.23	0.21	0.2	0.18
% over 64 years of age	0.13	0.13	0.13	0.12
% manufacturing	0.16	0.18	0.21	0.2
% construction	0.06	0.056	0.057	0.05
% wholesale trade	0.047	0.045	0.04	0.03
% retail trade	0.14	0.15	0.16	0.15
% finance-insurance-real estate	0.08	0.07	0.06	0.05
% public administration	0.036	0.04	0.04	0.05
% education services	0.087	0.08	0.07	0.08
% health services	0.1	0.096	0.09	0.11

Note: Average characteristics for neighborhoods in each of four quartiles of the neighborhood unemployment distribution.

a *frictional* level of unemployment: that is, one in which all unemployed individuals are voluntarily between jobs. The rate of unemployment in the top quartile, however, shows greater variability across the four cities. In Little Rock, for example, neighborhoods in the highest quartile have an average unemployment rate of 11 percent. In Louisville, Memphis and St. Louis, they average, respectively, 13.6 percent, 18.1 percent and 15.2 percent.

The various characteristics of neighborhoods within each quartile show many of the patterns that the results in Table 2 revealed. Neighborhoods with lower rates of joblessness, for instance, tend to be characterized by households with higher average incomes and more education, as well as greater fractions of married, white and older individuals (i.e., higher fractions of workers between 25 and 64 as opposed to 24 and under). They also tend to have relatively fewer workers employed in manufacturing, but more in finance-insurance-real estate. There is also some evidence that workers residing in low-unemployment neighborhoods have somewhat shorter commutes to work, at least in the sense that these neighborhoods have larger fractions of households with commutes between 20 and 29 minutes and smaller fractions with commutes in excess of an hour.

Three Theories of Rising Concentration

Now that we have a sense of the differences that exist between high- and low-unemployment neighborhoods, let us turn our attention to why the concentration of unemployment has risen in recent decades. In this section, three straightforward theories are considered, based partially on the results documented above, that might help to explain this trend: the movement of city populations toward suburban areas (sprawl), changes in industrial composition and union activity, and rising segregation of individuals by income and education.

Sprawl

One of the most prominent theories in the field of urban economics over the past half century suggests that the movement of population and employment away from city centers toward suburban locales has created an underclass of unemployed workers in central cities. This idea, known widely as the spatial mismatch hypothesis, was first studied by the economist John Kain (1968).

The basic rationale behind this theory is straightforward. As city populations and employers move away from traditional central business districts, it becomes more difficult for workers who remain in those central cities to find and secure jobs. Increased spatial isolation from employment opportunities, presumably, increases commuting costs and makes the job search process more difficult. In addition, increased distance may limit access to information about available jobs or create negative attitudes about central city workers among employers. Thus, as employers move farther away, it becomes less likely that residents of historical city centers will be able to locate and maintain a job.

Although the evidence on this theory is somewhat mixed, most studies of spatial mismatch provide some support for the idea. A study by Bruce Weinberg (2000) finds that job centralization, measured by the fraction of jobs located within the central city of a metropolitan area (relative to the fraction of residents in the central city), has a strong positive association with the employment rate of black workers who, on average, represent large fractions of inner-city dwellers. Similarly, the economists Keith Ihlanfeldt and David Sjoquist (1989) find that the earnings of both black and white low-skill workers tend to decrease with job decentralization, which is consistent with the idea that sprawl has made it more difficult for individuals in certain neighborhoods to find work.

Just looking at the results in Table 2, it seems that longer average commutes for residents of a neighborhood correspond to higher average rates of unemployment within that neighborhood. If longer commutes are indeed a direct consequence of sprawl, the results in Table 2 provide further support for the spatial mismatch conjecture.

To evaluate whether sprawl has influenced the residential concentration of unemployment, we need some way to measure it. Quantifying sprawl, however, tends to be difficult because the term does not have a precise definition. However, there are a variety of measures that attempt to capture the basic concept: that of individuals and employers moving from dense cores toward less populated suburban peripheries. Such measures include the fraction of a metropolitan area's population or employment located in a central city, the fraction within certain distances of the historical city center, or overall metropolitan area density. As it happens, many of these measures turn out to be positively correlated with one another. (See Glaeser and Kahn, 2004.)

This study quantifies urban decentralization within a metropolitan area using population density, which is constructed as a weighted average of block-group-level densities. The weights in this case are given by each block group's share of total metropolitan area population. Therefore, a metropolitan area's density is taken to be the density of the block group in which the average resident lives. Because suburban locales tend to have much lower residential densities than urban cores, lower levels of population density ought to be associated with more extensive sprawl.[10]

Summary statistics describing levels of population density among the 361 metropolitan areas in the sample in each year appear in Table 4. Between 1980 and 2000, the average metropolitan area saw its density decrease from 3,080 residents per square mile to 3,004 residents per square mile. Although average density did increase slightly during the 1980s, it dropped during the 1990s, leaving the residential density faced by a typical metropolitan resident lower in 2000 than two decades earlier.[11] This pattern is generally consistent with the long-standing trend over the past century for U.S. populations to spread out geographically.

Industrial Shifts and Unionization

The last several decades have been characterized by decreasing employment in certain sectors, but increasing employment in others. Most notably, manufacturing employment has decreased while service employment has increased. In addition, unionization rates have fallen substantially.

Some of these changes can be seen in the summary statistics reported in Table 4. Between 1980 and 2000, the average share of manufacturing in total employment declined from 22 percent to 14 percent across the 361 metropolitan areas in the sample, whereas the fractions of workers employed in education and health services rose from 17 percent to 20 percent. Unionization rates decreased from an average of 24 percent in 1980 to 14 percent in 2000.

How might these changes influence the geographic distribution of unemployment within a metropolitan area?

If workers in certain neighborhoods tend to be employed in similar types of industries, or if unionization is relatively concentrated among residents of certain neighborhoods, these changes may have produced differential rates of unemployment across different areas within a city. In other words, rather than there having been a change in the way that residents of a metropolitan area sort themselves across neighborhoods (e.g., into areas populated primarily by either high-skill workers or low-skill workers), it may simply be that changes in the labor market have differentially influenced workers of different neighborhoods.

Based on the results in Table 2, for example, larger fractions of workers within a neighborhood who are employed in manufacturing tend to be associated with higher unemployment rates. Larger fractions of workers in finance-insurance-real estate, by contrast, correspond to lower unemployment rates. The change in the industrial makeup of a metro area's economy, then, might help explain the trend in neighborhood unemployment.

Segregation by Income and Education

The rise in the extent of concentration of unemployment may, on the other hand, be the product of greater segregation of individuals by income and education. Recall from Table 2, unemployment shows a very strong association with both income and education. If the manner by which individuals sort themselves into residential areas

Table 4. Summary Statistics: Metropolitan Area Characteristics

Year	Variable	Mean	Standard Deviation	Minimum	Maximum
1980	population density	3,080.4	2,508.9	349.4	34,719.7
	% manufacturing	0.22	0.1	0.03	0.54
	% agriculture, forestry, fisheries	0.05	0.04	0.006	0.24
	% construction	0.06	0.02	0.03	0.15
	% wholesale trade	0.04	0.01	0.01	0.09
	% retail trade	0.17	0.02	0.11	0.24
	% finance-insurance-real estate	0.05	0.02	0.02	0.14
	% public administration	0.06	0.04	0.2	0.28
	% education services	0.1	0.04	0.05	0.38
	% health services	0.07	0.02	0.03	0.22
	unionization rate	0.24	0.08	0.09	0.37
	education segregation	0.29	0.07	0.026	0.49
	income segregation	0.07	0.04	0.003	0.24
1990	population density	3,083.4	2,613.2	607.1	35,993.8
	% manufacturing	0.18	0.08	0.03	0.48
	% agriculture, forestry, fisheries	0.04	0.03	0.008	0.19
	% construction	0.06	0.02	0.04	0.12
	% wholesale trade	0.04	0.01	0.01	0.11
	% retail trade	0.18	0.02	0.12	0.26
	% finance-insurance-real estate	0.06	0.02	0.03	0.16
	% public administration	0.05	0.03	0.2	0.22
	% education services	0.09	0.04	0.05	0.38
	% health services	0.09	0.02	0.04	0.22
	unionization rate	0.17	0.07	0.06	0.32
	education segregation	0.34	0.06	0.19	0.51
	income segregation	0.135	0.05	0.04	0.31
2000	population density	3,004.1	2,674.6	641.7	37,377.7
	% manufacturing	0.14	0.07	0.02	0.44
	% agriculture, forestry, fisheries	0.02	0.02	0.002	0.15
	% construction	0.07	0.01	0.03	0.13
	% wholesale trade	0.03	0.008	0.01	0.08
	% retail trade	0.12	0.01	0.08	0.17
	% finance-insurance-real estate	0.06	0.02	0.03	0.2
	% public administration	0.05	0.03	0.02	0.19
	% education services	0.09	0.04	0.05	0.37
	% health services	0.11	0.02	0.06	0.27
	unionization rate	0.14	0.06	0.04	0.27
	education segregation	0.33	0.056	0.19	0.47
	income segregation	0.13	0.05	0.02	0.38

Note: unweighted statistics calculated from 361 metropolitan areas in each year.

has created neighborhoods with concentrations of either high- or low-skill individuals, there should be an increasing disparity between the unemployment rates of different neighborhoods. Low-skill individuals, after all, tend to experience higher rates of unemployment than high-skill individuals.[12]

On the surface, this explanation seems related to the urban decentralization hypothesis sketched above. Indeed, previous work has suggested that as city populations spread out, households become increasingly sorted into high- and low-income neighborhoods. (See Glaeser and Kahn, 2004.) Recent work, however, challenges this view. In particular, my own work (Wheeler, 2006) finds little association between the extent to which urban populations spread out and the income differentials they exhibit across either block groups or tracts.

To quantify income segregation, this study computes the extent of variation between block groups as follows:

$$(2) \quad \textit{Income Variation} = \sum_{i=1}^{N} \omega_i (\bar{y}_i - \bar{y})^2$$

where $\bar{y}_i$ is the average household income of block group i, $\bar{y}$ is the average household income in the city, ω_i is the share of the metropolitan area's households living in block group i, and N is the number of neighborhoods in the metropolitan area. This quantity reflects the extent of heterogeneity in the average income levels of different residential areas.

To measure educational segregation, this study computes an index of dissimilarity for college graduates.[13] Recall, the resulting values represent the fraction of a city's population with a bachelor's degree or more that would have to move for these individuals to be uniformly distributed throughout the city.

Summary statistics describing the evolution of these two segregation measures are shown in Table 4. Clearly, both quantities increased between 1980 and 2000. On average, the amount of between-neighborhood income variation nearly doubled over this period, although essentially all of the increase took place during the 1980s. The dissimilarity index for college graduates rose from 0.29 to 0.34 between 1980 and 1990. It then showed a modest decline during the 1990s, dropping to 0.33 by 2000.

Primary Statistical Results

To test the hypotheses outlined above, the study considers the following statistical model in which the degree of neighborhood unemployment heterogeneity (or concentration) in city c in year t, s_{ct}, is expressed as follows:

$$(3) \quad s_{ct} = \delta_c + \delta_t + \beta X_{ct} + \varepsilon_{ct}$$

where δ_c is a city-specific effect intended to represent any time-invariant characteristics that may influence the extent of variation in unemployment across a city's neighborhoods (e.g., a long-standing history of residential segregation); δ_t is a year-specific effect designed to pick up time trends that influence all cities; X_{ct} is a vector of time-varying city-level characteristics; and ε_{ct} is a statistical residual.

The vector of characteristics, X_{ct}, includes the following: log population density, the proportion of the city's resident population that is female, the proportion that is black, the proportion foreign-born, the fraction of the population under the age of 25, the fraction over the age of 65, the share of total employment in each of nine broad sectors, the city's overall unemployment rate, the fraction of the city's labor force that is covered by a union contract, and measures of segregation of households by income and education across neighborhoods.[14] Three region dummies interacted with the year indicators, δ_t, are included.

Many of these variables are intended to account for some basic economic and demographic factors that may influence the distribution of unemployment within a city's neighborhoods.

Unemployment might, for example, vary significantly across neighborhoods as a result of the racial, gender or age composition of the local population. The results from Table 2 certainly suggest that these characteristics might be important. In addition, some neighborhoods may be more sensitive to changes in the local business cycle than others. Therefore, the unemployment rate and the six region-year interactions (e.g., an effect that captures being in the South in 1990 or the Midwest in 2000) are included to control for the influence of fluctuations in local and regional economic activity.

The remaining covariates are included to assess the hypotheses outlined earlier. In particular, population density is a rough proxy for urban decentralization; the industry shares and unionization rate quantify changes in the labor market facing workers; and the segregation measures represent the degree of income and educational sorting across a city's block groups.

The results appear in Table 5. Each column lists the coefficients for a particular measure of unemployment concentration. Beginning with the unemployment dissimilarity index in the first column of estimates, it is evident that a number of the demographic characteristics are significantly associated with the geographic concentration of unemployment. Cities with larger fractions of individuals either under 24 or over 65 years of age tend to have more unequal distributions of unemployed workers across neighborhoods. Cities in which these two groups are heavily represented may be strongly segregated by age. College towns, for instance, have large fractions of relatively young households clustered in certain neighborhoods. If these individuals also experience relatively high rates of unemployment, the dissimilarity index would be especially high in these cities. The significantly positive coefficient on the college fraction, which tends to be especially high in college towns, may reflect this same effect.

The results also suggest that a higher fraction of the resident population that is foreign-born corresponds to less unemployment concentration. This finding may simply indicate that cities with large numbers of immigrants have rapidly growing economies and, therefore, a low incidence of unemployment among all individuals. It could also reflect the fact that immigrants tend to be more active labor force participants than domestic workers, at least among those who have relatively little education (Aaronson et al, 2006).

Moving on to the three hypothetical causes for the rise in unemployment concentration, it is apparent that sprawl shows little systematic association with the dissimilarity index. The coefficient on the logarithm of population density is statistically negligible (i.e., we cannot say for certain whether the true value of the effect is positive, negative or equal to zero). Moreover, the estimated value is actually positive, suggesting that unemployment concentration is higher in more densely populated cities (those with less sprawl).

How do we reconcile this finding with those from Table 2, which indicate that longer commute times are associated with higher rates of unemployment? The data, quite simply, show a direct connection between density and average commute times. Therefore, more densely populated cities tend to be associated with longer commutes. Such a finding would be consistent with the idea that density is associated with greater use of public transportation. As shown in a study by Edward Glaeser and Matthew Kahn (2004), commute times on public transportation are roughly twice as long as those in which people drive.

In addition, the union coverage rate and five of the nine industry shares are insignificant. Moreover, based on the signs of the four significant industry share coefficients, none support the hypothesis sketched earlier. In particular, the decline of manufacturing and the rise of professional services (e.g., education) should be associated with the displacement of relatively low-skill workers but rising employment opportunities for high-skill workers. To the extent that these types of workers reside in different neighborhoods, these changes should generate greater concentration of unemployment. According to the results in Table 5, these changes tend to be associated with *decreases* in unemployment concentration.

Changes in the extent of residential segregation by income and education, by contrast, correlate strongly with changes in the geographic concentration of unemployment. There is, of course,

Table 5. Correlates of Unemployment Concentration

Regressor	Dependent Variable			
	Dissimilarity	90-10 Difference	90-50 Difference	50-10 Difference
% college	0.32* (0.09)	–0.17* (0.04)	–0.1* (0.04)	–0.08* (0.02)
% female	–0.35 (0.24)	–0.006 (0.11)	0.15 (0.1)	–0.16* (0.05)
% black	–0.1 (0.13)	0.12* (0.06)	0.14* (0.06)	–0.02 (0.03)
% under 24	0.43* (0.14)	–0.03 (0.07)	0.004 (0.06)	–0.03 (0.03)
% over 65	0.44* (0.17)	0.03 (0.08)	0.02 (0.07)	0.009 (0.04)
% foreign-born	–0.27* (0.08)	–0.03 (0.04)	–0.05 (0.04)	0.01 (0.02)
% manufacturing	0.18* (0.09)	–0.03 (0.04)	–0.02 (0.04)	–0.008 (0.02)
% agriculture, forestry, fisheries	0.27* (0.15)	0.1 (0.07)	0.07 (0.07)	0.03 (0.03)
% construction	0.33* (0.17)	–0.02 (0.08)	–0.005 (0.07)	–0.02 (0.04)
% wholesale trade	0.09 (0.22)	–0.001 (0.1)	0.05 (0.09)	–0.06 (0.05)
% retail trade	0.19 (0.13)	0.02 (0.06)	0.03 (0.06)	–0.02 (0.03)
% finance-insurance-real estate	0.27 (0.2)	–0.09 (0.1)	–0.06 (0.09)	–0.02 (0.04)
% public administration	0.25 (0.15)	–0.1 (0.07)	–0.01 (0.07)	–0.08* (0.03)
% education services	–0.4* (0.17)	0.14* (0.08)	0.08 (0.08)	0.06* (0.04)
% health services	0.07 (0.17)	0.14* (0.08)	0.11 (0.08)	0.03 (0.04)
unemployment rate	0.23* (0.11)	0.96* (0.05)	0.64* (0.05)	0.33* (0.02)
unionization rate	0.03 (0.07)	0.05 (0.03)	0.04 (0.03)	0.016 (0.014)
education segregation	0.25* (0.05)	0.1* (0.02)	0.05* (0.02)	0.05* (0.01)
income segregation	0.42* (0.07)	0.18* (0.03)	0.14* (0.03)	0.04* (0.014)
log population density	0.016 (0.011)	–0.004 (0.005)	–0.002 (0.005)	–0.002 (0.002)
R-squared	0.66	0.71	0.58	0.59

Note: Standard errors are reported in parentheses. All regressions include time dummies for the years 1980 and 1990 and interactions of these dummies with three Census region indicators. An asterisk (*) represents significance at 10 percent or better.

likely to be some "endogeneity" associated with the income segregation variable (i.e., it is probably determined by unemployment concentration). After all, as the distribution of unemployed households becomes more uneven within a metropolitan area, the distribution of income will likely become more uneven, too, because income tends to be strongly tied to employment status.

As a result, the coefficient on income segregation likely overstates the extent to which greater income segregation *causes* unemployment concentration to rise. Nevertheless, the positive association between these two quantities is at least broadly consistent with the income-sorting hypothesis.

Moreover, the estimates also demonstrate a significant connection between unemployment concentration and the segregation of college graduates, which is less obviously endogenous with respect to the dependent variable. Unlike income differentials across neighborhoods, there is little reason to believe that an increase in the concentration of unemployed households should cause highly educated households to become more segregated residentially.

The estimates in the next three columns of Table 5, where the dependent variables are the unemployment percentile differences, offer many of the same conclusions. The greater the change in the extent of between-neighborhood income variation or the separation of college graduates from individuals with less education, the larger the differentials in the unemployment rates of different residential areas. Neither the unionization rate nor the log of population density shows a significant association with any of the differentials, and only a few of the industry shares produce significant coefficients.

As one might expect, changes in a metropolitan area's overall unemployment rate are strongly associated with the dissimilarity index and all three unemployment rate differentials, suggesting that the local business cycle is an important determinant of the geographic distribution of unemployment.

Again, if economic downturns simply affect workers in certain neighborhoods (say, low-skill workers in relatively low-income areas) more than others, then one would expect to see all four measures of unemployment concentration move directly with the overall rate of unemployment. That is precisely what the estimates in Table 5 indicate. Interestingly, however, even after having accounted for this effect, there remains strong evidence that rising concentration of unemployment has been driven by changes in the extent to which households are segregated by income and education. Thus, although local business cycle effects are clearly important, they cannot completely account for trends in neighborhood-level unemployment. We should not be surprised by this result because, as noted previously, average overall rates of unemployment actually fell in the metropolitan areas of the United States between 1980 and 2000, when the neighborhood-level concentration of unemployment rose.

Results Using Weighted Percentiles

Because the percentiles used above are computed in an unweighted fashion, it is possible that they provide misleading inferences about the extent to which unemployed workers are spatially concentrated. For example, certain block groups may be extremely small, possessing only a few households, the majority of whom happen to be unemployed. These block groups may then help to create extremely large values for a 90-10 or 50-10 difference. Yet, because they only contain an extremely small share of a metropolitan area's total stock of unemployed individuals, unemployment concentration might, in actuality, be somewhat modest in this metro area.

A similar problem does not influence the dissimilarity index because, as shown in equation (1), the index implicitly gives less weight to block groups with smaller numbers of employed and unemployed individuals. Therefore, an extremely small block group with a very high unemployment rate will contribute relatively little to the index value because its shares of unemployed and employed workers will be small.

In this section, we examine weighted percentiles, where the weights are given by the size of each block group's labor force. After computing these percentiles, we simply created 90-10, 90-50 and 50-10 differences and estimate the same regressions as those reported in Table 5.

Summary statistics indicate that these weighted measures of unemployment concentration did rise, although not as sharply as the unweighted measures. On average, the 90-10, 90-50 and 50-10 differences stood at 6.9, 4.4 and 2.6 percentage points in 1980. By 2000, they had risen to 9.6, 6.5 and 3.1 percentage points.

Regression results for these weighted differentials are presented in Table 6. For the most part, they generate similar conclusions to those drawn earlier. There is little evidence of the importance of industrial shifts and changes in union activity. Population density does, in this case, show a significant association with the 90-10 and 90-50 differences. However, the coefficients are positive, indicating that rising sprawl (i.e., falling density) is associated with less unemployment concentration rather than more.

On the other hand, there is once again strong evidence that the rising segregation of individuals by educational attainment—specifically, the separation of college graduates from those with less education— and increasing income variation across block groups are associated with rising unemployment concentration. Cities characterized by larger increases in residential sorting along these two dimensions have seen, on average, larger increases in their levels of unemployment concentration.

Another Look at the Eighth District

Given these results, let us return to the four metro areas from the Federal Reserve's Eighth District: Little Rock, Louisville, Memphis and St. Louis. Tables 7A-7D summarize values of several variables considered in the statistical work for each of the three years in the data: education segregation, income segregation, population density and the overall rate of unemployment. The tables also report values of the unemployment dissimilarity index and three percentile differences (90-10, 90-50, 50-10).

There are some clear patterns that emerge from these statistics.

First, there was a general increase in segregation by both education and income between 1980 and 2000, although the majority of this increase (if not all, as in most of the cases) took place between 1980 and 1990. Second, population density has shown a consistent decline in all four metropolitan areas. Third, the overall city-level unemployment rate decreased between 1980 and 2000 (although it increased slightly during the 1980s in Little Rock). Finally, the four measures of unemployment concentration tend to show, as a group, a growing disparity in joblessness across neighborhoods between 1980 and 2000, although the increase was larger in the 1980s than 1990s.

Based on these patterns, the direct connection between segregation by income and education and the concentration of unemployment established in Tables 5 and 6 is understandable. Indeed, all of these quantities increased sharply during the 1980s. The following decade, the rise in unemployment concentration slowed, especially when measured by the change in the percentile differences. This result, of course, coincides with a decrease in the extent of educational and income segregation.

The correspondence between these variables, however, is far from perfect. Although the patterns are reasonably clean in the 1980s, the data seem to show that the neighborhood-level segregation of college graduates and the amount of between-neighborhood income variation decreased during the 1990s, even as unemployment concentration continued to rise. The discrepancy between the strong correlation between these two quantities and the four measures of unemploy-

Table 6. Correlates of Weighted Percentile Differences

Regressor	Dependent Variable			
	Dissimilarity	90-10 Difference	90-50 Difference	50-10 Difference
% college	–0.13* (0.04)	–0.07* (0.04)	–0.06* (0.02)	–0.08* (0.02)
% female	0.09 (0.09)	0.14 (0.1)	–0.05 (0.05)	–0.16* (0.05)
% black	0.004 (0.05)	0.05 (0.05)	–0.04* (0.03)	–0.02 (0.03)
% under 24	0.05 (0.05)	0.07 (0.05)	–0.02 (0.03)	–0.03 (0.03)
% over 65	0.06 (0.07)	0.03 (0.07)	0.02 (0.03)	0.009 (0.04)
% foreign-born	–0.02 (0.03)	–0.04 (0.03)	0.02 (0.02)	0.01 (0.02)
% manufacturing	0.007 (0.04)	–0.005 (0.03)	0.01 (0.02)	–0.008 (0.02)
% agriculture, forestry, fisheries	0.05 (0.06)	0.009 (0.06)	0.04 (0.03)	0.03 (0.03)
% construction	0.02 (0.07)	–0.006 (0.07)	0.02 (0.03)	–0.02 (0.04)
% wholesale trade	–0.015 (0.09)	0.000004 (0.08)	–0.01 (0.04)	–0.06 (0.05)
% retail trade	0.06 (0.05)	0.04 (0.05)	0.02 (0.03)	–0.02 (0.03)
% finance-insurance-real estate	–0.07 (0.08)	–0.01 (0.08)	–0.06 (0.04)	–0.02 (0.04)
% public administration	–0.007 (0.06)	0.006 (0.06)	–0.01 (0.03)	–0.08* (0.03)
% education services	0.07 (0.07)	0.001 (0.07)	0.07* (0.03)	0.06* (0.04)
% health services	0.16* (0.07)	0.14* (0.07)	0.02 (0.03)	0.03 (0.04)
unemployment rate	0.94* (0.05)	0.63* (0.04)	0.3* (0.02)	0.33* (0.02)
unionization rate	–0.01 (0.03)	–0.02 (0.03)	0.006 (0.01)	0.016 (0.014)
education segregation	0.09* (0.02)	0.04* (0.02)	0.05* (0.01)	0.05* (0.01)
income segregation	0.13* (0.03)	0.11* (0.03)	0.02* (0.01)	0.04* (0.014)
log population density	0.01* (0.005)	0.008* (0.004)	0.003 (0.002)	–0.002 (0.002)
R-squared	0.78	0.65	0.55	0.59

Note: Standard errors are reported in parentheses. All regressions include time dummies for the years 1980 and 1990, and interactions of these dummies with three Census region indicators. An asterisk (*) represents significance at 10 percent or better.

ment concentration seen in Tables 5 and 6 and what we see in Table 7A-7D likely stems from the fact that the results in Tables 5 and 6 are based on 361 metro areas, whereas Tables 7A-7D are based upon single metro areas. What holds on average for the entire sample of cities will not necessarily hold for each one individually.

It should also be noted that, although the segregation of households by income and education likely contributed to the rise in unemployment concentration, it probably only accounts for part of the trend. That is, there are undoubtedly factors that this study does not consider that have also played an important role. Providing a complete description of why unemployment concentration has risen is extremely difficult (if not impossible), and this study makes no attempt to do so.

Table 7A. Selected Metropolitan Area Characteristics: Little Rock

Characteristic	1980	1990	2000
education segregation	0.357	0.39	0.392
income segregation	0.096	0.14	0.12
population density	2,553.6	2,264.9	1,791.5
overall unemployment	0.054	0.056	0.052
unemployment dissimilarity	0.21	0.27	0.36
90-10 difference	0.075	0.1	0.12
90-50 difference	0.041	0.067	0.086
50-10 difference	0.034	0.033	0.033

Table 7B. Selected Metropolitan Area Characteristics: Louisville

Characteristic	1980	1990	2000
education segregation	0.394	0.432	0.41
income segregation	0.124	0.196	0.177
population density	3,745.2	3,321.8	3,036.9
overall unemployment	0.08	0.061	0.046
unemployment dissimilarity	0.208	0.292	0.324
90-10 difference	0.103	0.115	0.105
90-50 difference	0.065	0.08	0.075
50-10 difference	0.039	0.035	0.03

Table 7C. Selected Metropolitan Area Characteristics: Memphis

Characteristic	1980	1990	2000
education segregation	0.381	0.436	0.424
income segregation	0.172	0.293	0.23
population density	4,288.2	3,751.7	3,361.9
overall unemployment	0.079	0.074	0.065
unemployment dissimilarity	0.278	0.361	0.387
90-10 difference	0.13	0.165	0.171
90-50 difference	0.093	0.12	0.12
50-10 difference	0.038	0.045	0.051

Table 7D. Selected Metropolitan Area Characteristics: St. Louis

Characteristic	1980	1990	2000
education segregation	0.33	0.39	0.388
income segregation	0.096	0.18	0.173
population density	4,721.4	4,063.3	3,557.6
overall unemployment	0.078	0.064	0.055
unemployment dissimilarity	0.221	0.336	0.363
90-10 difference	0.114	0.162	0.152
90-50 difference	0.079	0.124	0.116
50-10 difference	0.035	0.038	0.035

Conclusions and Policy Considerations

This paper has documented a rise in the extent to which unemployed households throughout 361 U.S. metropolitan areas have become concentrated residentially.

Whereas in 1980, the median unemployed worker resided in a neighborhood with an unemployment rate of 7.5 percent, by 2000, the unemployment rate of this worker's neighborhood was 7.9 percent. Again, this is particularly striking because, on average, unemployment rates were lower in 2000 than in 1980. Other measures of residential concentration of the unemployed—an index of dissimilarity and differences among three percentiles (either weighted or unweighted) of the neighborhood unemployment distribution—show similar qualitative trends. Therefore, although the overall rate of unemployment has not trended upward over time, there is evidence of an upward trend in the spatial concentration of the unemployed within the country's urban labor markets.

Among three plausible explanations, this study found the greatest support for the idea that increased segregation of households by income and educational attainment underlies this trend. There is less consistent evidence that sprawl or structural changes in the labor market are responsible.

As noted previously, these results are especially interesting because the literature on neighborhood effects suggests that a number of labor market outcomes are tied to the characteristics of one's place of residence. Indeed, following this general premise, rising unemployment concentration may help to account for two additional trends that have been observed in the United States over the past three decades: (1) rising inequality in both income and earnings and (2) an increase in the expected duration of unemployment. Both are, by now, well-documented.

Between 1971 and 1995, the amount by which the 90th percentile of the U.S. wage distribution exceeded the 10th percentile grew from 266 percent to 366 percent (Acemoglu, 2002).[15] This increase has been accompanied by growing dispersion among the earnings of individuals of different skill groups (e.g., as defined by education and experience) as well as of those within the same group. Although there has not been a long-run trend in the overall rate of unemployment, a study by Katharine Abraham and Robert Shimer (2001) reports that the mean unemployment duration rose by roughly 20 percent (from 10 weeks to 12 weeks) between 1980 and 2000. Much of this rise can be linked to an increase in very long-term unemployment (more than 26 weeks), which has more than tripled as a share of the labor force since 1969.

As one might expect, research studying these two patterns has identified some of the most likely culprits. Rising inequality is likely related to skill-biased technological change, changes in the institutional makeup of the labor market (e.g., declining union activity and a stagnating real minimum wage) and growth in international trade and immigration.

Longer spells of unemployment are probably tied to demographic changes, especially the aging of the working population and an increase in the fraction of women participating in the labor force. Older workers and women tend to experience somewhat longer periods of unemployment (Abraham and Shimer, 2001).

Very little work, however, has considered that there may be a spatial aspect to these phenomena. With rising concentration of the unemployed, workers in search of a job might find it increasingly difficult to locate one. Recall, Giorgio Topa's (2001) study reports evidence consistent with local spillovers in unemployment status across Census tracts in Chicago. Again, this result may be the product of an adverse network effect (i.e., if workers find jobs through neighborhood contacts) or of employers simply avoiding workers from high-unemployment neighborhoods due to a social stigma.

A rising concentration of unemployment in certain neighborhoods may, then, give rise to growing unemployment durations among workers living in these neighborhoods and further decrease their income and labor earnings relative to the rest of the labor force over time.

It is interesting to note that, over the sample period studied here, the majority of the increase in the geographic concentration of unemployment took place during the 1980s when much of the rise in both income inequality and unemployment duration took place. Although far from conclusive, the fact that the timing of these phenomena matches closely certainly suggests that there may be a connection among them.

Such results may have important implications for addressing unemployment. Currently, there are a number of both public and private programs that try to help individuals find work. These programs include unemployment insurance, job training and employment agencies. For the most part, these programs assist people who do not have jobs, either by connecting them with employers who have vacancies or by helping them acquire skills that they believe employers require.

However, the discussion above suggests that a worker's ability to find and maintain employment might also be affected by the extent of joblessness in his or her neighborhood. Consequently, policymakers interested in reducing unemployment within a metropolitan area may wish to investigate strategies that attempt to reduce the extent to which the unemployed are residentially isolated. Although it is difficult to influence where people with different levels of education and income choose to reside, programs that attempt to achieve greater heterogeneity within residential areas could certainly help prevent areas of extreme unemployment and poverty from forming.

Revitalizing downtowns, for example, might help draw high-income, highly educated residents to areas that suffer from high unemployment. Doing so may also help the unemployed find work by providing greater numbers of jobs close by. Recall, although population density did not show a significant association with unemployment concentration, a neighborhood's unemployment rate is strongly tied to the average commute times of its residents.

In addition, programs aimed at helping residents of impoverished areas relocate to more economically successful neighborhoods might also help. Policies that encourage mixed-income housing—that is, those that set aside certain fractions of new housing units for low- to moderate-income households—may also help individuals who face a high risk of unemployment.

These, of course, are just a few hypothetical strategies that require a great deal more research before any formal policy recommendations could be made. However, the notion that the residential concentration of unemployment probably represents a significant aspect of the unemployment problem in the United States is one to which policymakers should give some serious consideration. The fact that this problem seems to have grown worse in recent decades suggests that the costs of not doing so are rising.

Appendix– Metropolitan Areas

Abilene, TX
Akron, OH
Albany, GA
Albany-Schenectady-Troy, NY
Albuquerque, NM
Alexandria, LA
Allentown-Bethlehem-Easton, PA-NJ
Altoona, PA
Amarillo, TX
Ames, IA
Anchorage, AK
Anderson, IN
Anderson, SC
Ann Arbor, MI
Anniston-Oxford, AL
Appleton, WI
Asheville, NC
Athens-Clarke County, GA
Atlanta-Sandy Springs-Marietta, GA
Atlantic City, NJ
Auburn-Opelika, AL
Augusta-Richmond County, GA-SC
Austin-Round Rock, TX
Bakersfield, CA
Baltimore-Towson, MD
Bangor, ME
Barnstable Town, MA
Baton Rouge, LA
Battle Creek, MI
Bay City, MI
Beaumont-Port Arthur, TX
Bellingham, WA
Bend, OR
Billings, MT
Binghamton, NY
Birmingham-Hoover, AL
Bismarck, ND
Blacksburg-Christiansburg-Radford, VA
Bloomington, IN
Bloomington-Normal, IL
Boise City-Nampa, ID
Boston-Cambridge-Quincy, MA-NH
Boulder, CO
Bowling Green, KY
Bremerton-Silverdale, WA
Bridgeport-Stamford-Norwalk, CT
Brownsville-Harlingen, TX
Brunswick, GA
Buffalo-Niagara Falls, NY
Burlington, NC
Burlington-South Burlington, VT
Canton-Massillon, OH
Cape Coral-Fort Myers, FL
Carson City, NV
Casper, WY
Cedar Rapids, IA
Champaign-Urbana, IL
Charleston, WV
Charleston-North Charleston, SC
Charlotte-Gastonia-Concord, NC-SC
Charlottesville, VA
Chattanooga, TN-GA
Cheyenne, WY
Chicago-Naperville-Joliet, IL-IN-WI
Chico, CA
Cincinnati-Middletown, OH-KY-IN
Clarksville, TN-KY
Cleveland, TN
Cleveland-Elyria-Mentor, OH
Coeur d'Alene, ID
College Station-Bryan, TX
Colorado Springs, CO
Columbia, MO
Columbia, SC
Columbus, GA-AL
Columbus, IN
Columbus, OH
Corpus Christi, TX
Corvallis, OR
Cumberland, MD-WV
Dallas-Fort Worth-Arlington, TX
Dalton, GA
Danville, IL
Danville, VA
Davenport-Moline-Rock Island, IA-IL
Dayton, OH
Decatur, AL
Decatur, IL
Deltona-Daytona Beach-Ormond Beach, FL
Denver-Aurora, CO

Des Moines, IA
Detroit-Warren-Livonia, MI
Dothan, AL
Dover, DE
Dubuque, IA
Duluth, MN-WI
Durham, NC
Eau Claire, WI
El Centro, CA
El Paso, TX
Elizabethtown, KY
Elkhart-Goshen, IN
Elmira, NY
Erie, PA
Eugene-Springfield, OR
Evansville, IN-KY
Fairbanks, AK
Fargo, ND-MN
Farmington, NM
Fayetteville, NC
Fayetteville-Springdale-Rogers, AR-MO
Flagstaff, AZ
Flint, MI
Florence, SC
Florence-Muscle Shoals, AL
Fond du Lac, WI
Fort Collins-Loveland, CO
Fort Smith, AR-OK
Fort Walton Beach-Crestview-Destin, FL
Fort Wayne, IN
Fresno, CA
Gadsden, AL
Gainesville, FL
Gainesville, GA
Glens Falls, NY
Goldsboro, NC
Grand Forks, ND-MN
Grand Junction, CO
Grand Rapids-Wyoming, MI
Great Falls, MT
Greeley, CO
Green Bay, WI
Greensboro-High Point, NC
Greenville, NC
Greenville, SC
Gulfport-Biloxi, MS
Hagerstown-Martinsburg, MD-WV
Hanford-Corcoran, CA
Harrisburg-Carlisle, PA
Harrisonburg, VA
Hartford-West Hartford-East Hartford, CT
Hattiesburg, MS
Hickory-Lenoir-Morganton, NC
Hinesville-Fort Stewart, GA
Holland-Grand Haven, MI
Honolulu, HI
Hot Springs, AR
Houma-Bayou Cane-Thibodaux, LA
Houston-Sugar Land-Baytown, TX
Huntington-Ashland, WV-KY-OH
Huntsville, AL
Idaho Falls, ID
Indianapolis, IN
Iowa City, IA
Ithaca, NY
Jackson, MI
Jackson, MS
Jackson, TN
Jacksonville, FL
Jacksonville, NC
Janesville, WI
Jefferson City, MO
Johnson City, TN
Johnstown, PA
Jonesboro, AR
Joplin, MO
Kalamazoo-Portage, MI
Kankakee-Bradley, IL
Kansas City, MO-KS
Kennewick-Richland-Pasco, WA
Killeen-Temple-Fort Hood, TX
Kingsport-Bristol-Bristol, TN-VA
Kingston, NY
Knoxville, TN
Kokomo, IN
La Crosse, WI-MN
Lafayette, IN
Lafayette, LA
Lake Charles, LA
Lakeland, FL
Lancaster, PA
Lansing-East Lansing, MI
Laredo, TX
Las Cruces, NM
Las Vegas-Paradise, NV
Lawrence, KS

Lawton, OK
Lebanon, PA
Lewiston, ID-WA
Lewiston-Auburn, ME
Lexington-Fayette, KY
Lima, OH
Lincoln, NE
Little Rock-North Little Rock, AR
Logan, UT-ID
Longview, TX
Longview, WA
Los Angeles-Long Beach-Santa Ana, CA
Louisville, KY-IN
Lubbock, TX
Lynchburg, VA
Macon, GA
Madera, CA
Madison, WI
Manchester-Nashua, NH
Mansfield, OH
McAllen-Edinburg-Mission, TX
Medford, OR
Memphis, TN-MS-AR
Merced, CA
Miami-Fort Lauderdale-Miami Beach, FL
Michigan City-La Porte, IN
Midland, TX
Milwaukee-Waukesha-West Allis, WI
Minneapolis-St. Paul-Bloomington, MN-WI
Missoula, MT
Mobile, AL
Modesto, CA
Monroe, LA
Monroe, MI
Montgomery, AL
Morgantown, WV
Morristown, TN
Mount Vernon-Anacortes, WA
Muncie, IN
Muskegon-Norton Shores, MI
Myrtle Beach-Conway-North Myrtle Beach, SC
Napa, CA
Naples-Marco Island, FL
Nashville-Davidson-Murfreesboro, TN
New Haven-Milford, CT
New Orleans-Metairie-Kenner, LA
New York-Northern New Jersey-Long Island, NY-NJ-PA
Niles-Benton Harbor, MI
Norwich-New London, CT
Ocala, FL
Ocean City, NJ
Odessa, TX
Ogden-Clearfield, UT
Oklahoma City, OK
Olympia, WA
Omaha-Council Bluffs, NE-IA
Orlando-Kissimmee, FL
Oshkosh-Neenah, WI
Owensboro, KY
Oxnard-Thousand Oaks-Ventura, CA
Palm Bay-Melbourne-Titusville, FL
Panama City-Lynn Haven, FL
Parkersburg-Marietta-Vienna, WV-OH
Pascagoula, MS
Pensacola-Ferry Pass-Brent, FL
Peoria, IL
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD
Phoenix-Mesa-Scottsdale, AZ
Pine Bluff, AR
Pittsburgh, PA
Pittsfield, MA
Pocatello, ID
Port St. Lucie-Fort Pierce, FL
Portland-South Portland-Biddeford, ME
Portland-Vancouver-Beaverton, OR-WA
Poughkeepsie-Newburgh-Middletown, NY
Prescott, AZ
Providence-New Bedford-Fall River, RI-MA
Provo-Orem, UT
Pueblo, CO
Punta Gorda, FL
Racine, WI
Raleigh-Cary, NC
Rapid City, SD
Reading, PA
Redding, CA
Reno-Sparks, NV
Richmond, VA
Riverside-San Bernardino-Ontario, CA
Roanoke, VA
Rochester, MN
Rochester, NY
Rockford, IL
Rocky Mount, NC
Rome, GA

Sacramento-Arden-Arcade-Roseville, CA
Saginaw-Saginaw Township North, MI
Salem, OR
Salinas, CA
Salisbury, MD
Salt Lake City, UT
San Angelo, TX
San Antonio, TX
San Diego-Carlsbad-San Marcos, CA
San Francisco-Oakland-Fremont, CA
San Jose-Sunnyvale-Santa Clara, CA
San Luis Obispo-Paso Robles, CA
Sandusky, OH
Santa Barbara-Santa Maria, CA
Santa Cruz-Watsonville, CA
Santa Fe, NM
Santa Rosa-Petaluma, CA
Sarasota-Bradenton-Venice, FL
Savannah, GA
Scranton-Wilkes-Barre, PA
Seattle-Tacoma-Bellevue, WA
Sheboygan, WI
Sherman-Denison, TX
Shreveport-Bossier City, LA
Sioux City, IA-NE-SD
Sioux Falls, SD
South Bend-Mishawaka, IN-MI
Spartanburg, SC
Spokane, WA
Springfield, IL
Springfield, MA
Springfield, MO
Springfield, OH
St. Cloud, MN
St. George, UT
St. Joseph, MO-KS
St. Louis, MO-IL
State College, PA
Stockton, CA
Sumter, SC
Syracuse, NY
Tallahassee, FL
Tampa-St. Petersburg-Clearwater, FL
Terre Haute, IN
Texarkana, TX-Texarkana, AR
Toledo, OH
Topeka, KS
Trenton-Ewing, NJ
Tucson, AZ
Tulsa, OK
Tuscaloosa, AL
Tyler, TX
Utica-Rome, NY
Valdosta, GA
Vallejo-Fairfield, CA
Vero Beach, FL
Victoria, TX
Vineland-Millville-Bridgeton, NJ
Virginia Beach-Norfolk-Newport News, VA-NC
Visalia-Porterville, CA
Waco, TX
Warner Robins, GA
Washington-Arlington-Alexandria, DC-VA-MD-WV
Waterloo-Cedar Falls, IA
Wausau, WI
Weirton-Steubenville, WV-OH
Wenatchee, WA
Wheeling, WV-OH
Wichita Falls, TX
Wichita, KS
Williamsport, PA
Wilmington, NC
Winchester, VA-WV
Winston-Salem, NC
Worcester, MA
Yakima, WA
York-Hanover, PA
Youngstown-Warren-Boardman, OH-PA
Yuba City, CA
Yuma, AZ

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Endnotes

[1] These are extremely small areas. In the year 2000, tracts encompassed roughly 1.3 square miles and 1,600 households on average, whereas block groups averaged approximately 0.33 square miles and 500 households.

[2] Case and Katz (1991) and Topa (2001) focus on estimating the strength of peer effects rather than documenting the evolution of segregation.

[3] These data are available at www.unionstats.com. Metropolitan area-level unionization rates are calculated as weighted averages of the state-level rates, where the weights are given by the fraction of each metro area's labor force located in each state.

[4] Metropolitan areas are the local labor markets examined throughout the analysis. The terms *city* and *metropolitan area* are used interchangeably for expositional purposes.

[5] The 90th percentile, for example, represents the unemployment rate that is greater than the unemployment rates of 90 percent of the block groups.

[6] This figure is calculated by taking a weighted median across all block groups within a metropolitan area, where the weights are the number of unemployed individuals within each block group.

[7] A list of metropolitan areas in the sample appears in the Appendix.

[8] The decrease in each percentile is very likely associated with the general decrease in unemployment during the 1990s. Recall, the average metropolitan area-level unemployment rate decreased from 6.4 percent to 5.9 percent between 1990 and 2000.

[9] That is, I estimate a series of regressions of the form: $y_{c,t} = \mu_c + \delta_t + \beta x_{c,t} + \varepsilon_{c,t},$ where $y_{c,t}$ is the unemployment rate in city c in year t, μ_c is a city-specific effect, δ_t is a year-specific effect, $x_{c,t}$ is the characteristic of interest (listed in Table 2), and $\varepsilon_{c,t}$ is a residual.

[10] In the year 2000, the average central city population density was 2,716 residents per square mile. Suburban densities that year averaged 208 residents per square mile. See Hobbs and Stoops (2002).

[11] Looking at median changes rather than mean changes, metropolitan area density actually decreased between 1980 and 1990. The median change was –75 residents per square mile, indicating that density actually decreased in the majority of metropolitan areas during the 1980s.

[12] For example, the Bureau of Labor Statistics reports that the average rate of unemployment tends to decrease with education attainment. See http://www.bls.gov/news.release/empsit.t04.htm.

[13] Studies of human capital and skills typically define an individual as having a high or low level of education based on whether he or she has a four-year college degree or not. Hence, I define educational segregation (i.e., the extent to which high- and low-education individuals do not live with one another) based on college completion.

[14] The nine industries are manufacturing; agriculture, forestry, fisheries; construction; wholesale trade; retail trade; finance-insurance-real estate; public administration; education services; and health services. Due to changes in the industrial classification system between 1990 and 2000, these were the only broad sectors that could be constructed on a consistent basis from the GeoLytics data.

[15] Similar evidence has been reported in many other studies, including Levy and Murnane (1992), Katz and Murphy (1992), and Juhn et al (1993).

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