Trends in Neighborhood-Level Unemployment in the United States: 1980 to 2000

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Although the average rate of unemployment across U.S. metropolitan areas declined between 1980 and 2000, the geographic concentration of the unemployed rose sharply over this period. That is, residential neighborhoods throughout the nation's metropolitan areas became increasingly divided into high- and low-unemployment areas. This paper documents this trend using data on more than 165,000 U.S. Census block groups (neighborhoods) in 361 metropolitan areas over the years 1980, 1990, and 2000; it also examines three potential explanations: (i) urban decentralization, (ii) industrial shifts and declining unionization, and (iii) increasing segregation by income and education. The results offer little support for either of the first two explanations. Rising residential concentration of the unemployed shows little association with changes in population density, industrial composition, or union activity. It does, however, show a significant association with both the degree of segregation according to income as well as education, suggesting that decreases in the extent to which individuals with different levels of income and education live in the same neighborhood may help account for this trend. (JEL J11, J64, R20, R23)

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The rate of unemployment 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, whereas 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 rate of unemployment.

Although 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] Hence, 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 households 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.

[1] As noted here, 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.

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However, what is 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 individuals' residential areas greatly influence their economic outcomes. Case and Katz (1991), for instance, find strong peer effects characterizing a variety of behaviors, including criminal activity, drug and alcohol use, schooling, and employment status within a sample of residential areas in Boston. Similarly, Topa (2001) 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. Wilson (1987) suggests that neighborhood effects of this sort form the basis of the rise in inner city poverty in the United States in recent decades. As successful workers have gradually left inner cities, 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 an important topic. However, although existing research has looked at residential segregation based on race (e.g., Cutler, Glaeser, and Vigdor, 1999) and income (e.g., Wheeler, 2006), relatively little work has studied the segregation of the unemployed from the employed.[2]

This paper seeks 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. The primary findings indicate that the extent to which unemployed workers are concentrated residentially increased dramatically over this period. For example, in 1980, the 90th percentile of the distribution of neighborhood unemployment rates averaged 11 percent over the 361 U.S. metropolitan areas in the sample, whereas the 10th percentile averaged 3.7 percent. By 2000, the 90th percentile had risen to 12.5 percent while the 10th percentile had dropped to 1.3 percent, suggesting that neighborhoods in the United States have become increasingly polarized into high- and low-unemployment areas.[3]

What accounts for this trend? Although these are not intended to be a comprehensive set of potential explanations, I consider three possibilities. First, the process of urban decentralization (i.e., the gradual movement of metropolitan populations in the United States from central cities to suburban locales) may have reduced the employment opportunities of households that continue to reside in historical city centers. That is, just as Wilson (1987) has argued, sprawl may have created a steadily rising gap between rates of unemployment in central cities and those in suburbs. Second, changes in the labor market, such as declining union activity and the shift of employment away from manufacturing toward other sectors, may have reduced the employment opportunities for workers in particular neighborhoods more so than it has for others. For instance, if a city's low- to middle-income neighborhoods are populated primarily by manufacturing workers, whereas the residents of its high-income neighborhoods are employed in professional services, a decline in the manufacturing sector (or a rise in the professional services sector) may result in a rising differential between neighborhood unemployment rates. Third, there may have been an increase in the extent to which skilled and unskilled workers are segregated across residential areas. That is, independent of either urban decentralization or shifts in union and industrial activity, the degree to which high- and low-skill workers live in the same neighborhoods may have decreased over time, thus leading to rising concentration of unemployment.

To summarize briefly, the findings offer little support for either of the first two explanations.

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

[3] These are unweighted statistics. If the percentiles are calculated by weighting each neighborhood by the size of its labor force, the average 90th percentile increased from 10.7 to 11.2 percent over this period while the 10th percentile dropped from 3.8 to 1.5 percent.

The change in the amount of unemployment concentration across neighborhoods shows little association with changes in population density (a proxy for urban decentralization), changes in the local rate of union coverage, or changes in the shares of employment accounted for by nine broad industrial sectors (including manufacturing). The results do, however, reveal a strong positive association between unemployment concentration and measures of segregation according to income and (college) education across neighborhoods. As such, the findings suggest that rising concentration of unemployment is related to an increase in the extent to which households have sorted themselves residentially by income and education.

DATA AND MEASUREMENT

The data are taken from the decennial U.S. Census of Population as compiled by GeoLytics.[4] These files identify a variety of characteristics of the households residing in a host of geographic units, including counties, tracts, and neighborhoods, 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 neighborhoods, 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, I create a number of variables at the metropolitan area–level, including population demographics, density (i.e., residents per square mile), and industrial composition. I also construct a rate of union coverage for each metropolitan area using the state-level rates reported by Hirsch, Macpherson, and Vroman (2001).[5] These quantities are intended to help identify the characteristics that are associated with changes in the geographic distribution of unemployment within a city.[6]

The primary object of interest—the degree to which unemployment is spatially concentrated—is measured in two fundamental ways. First, I compute the differences between three percentiles (90th, 50th, and 10th) of the distribution of neighborhood-level unemployment rates.[7] 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, I calculate an index of dissimilarity, which 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 given as follows:

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

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, Glaeser, and Vigdor (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) in order 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.

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4 More information about these data is available at www.geolytics.com.

5 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.

6 Metropolitan areas are the local labor markets examined throughout the analysis. The terms "city" and "metropolitan area" are used interchangeably for expositional purposes.

7 The 90th percentile, for example, represents the unemployment rate that is greater than the unemployment rates of 90 percent of the neighborhoods.

Table 1

Summary Statistics: Unemployment Concentration

Year	Variable	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

NOTE: Unweighted statistics calculated from 361 metropolitan areas in each year.

I define neighborhoods as block groups, which are the smallest geography for which detailed Census data are publicly available. As noted here previously, 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 neighborhood, then, can reasonably be expected to have some sort of interaction with one another (e.g., passing on the street). Conceptually, this feature of neighborhoods 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.

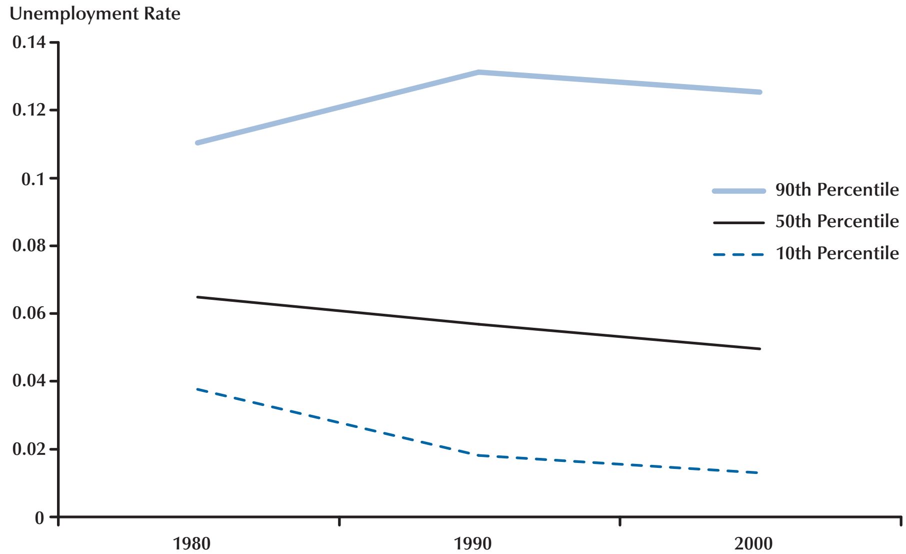
BASIC TRENDS

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 neighborhood with an unemployment rate of 7.5 percent (i.e., the unemployment rate within a worker's own neighborhood of residence was 7.5 percent or greater for at least 50 percent of all unemployed workers).[8] Two decades later, the median unemployed worker lived in a neighborhood with an unemployment

[8] This figure is calculated by taking a weighted median across all neighborhoods within a metropolitan area, where the weights are the number of unemployed individuals within each neighborhood.

Figure 1

Neighborhood Unemployment Percentiles



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 (1) and the percentile differentials. Summary statistics appear in Table 1.[9] 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 relocate in order 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 relocate in 2000 to equalize unemployment across all neighborhoods.

The percentile differences reveal a qualitatively similar pattern. In 1980, the average difference between the neighborhoods at the 90th and 10th percentiles of the unemployment distribution was 7.3 percentage points. 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 3 percentage points between 1980 and 2000, whereas the mean 50-10 gap increased by 1 percentage point.

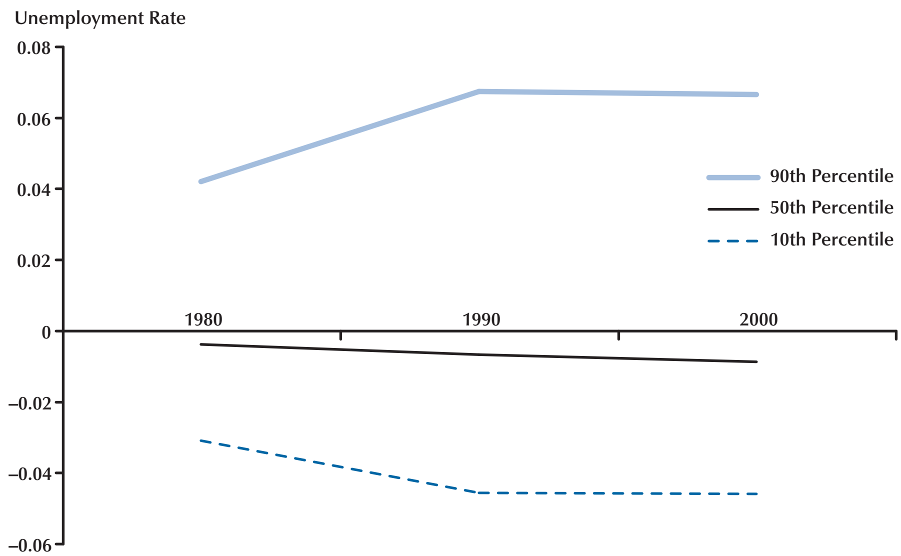
Figure 1 plots the average values of the 90th, 50th, and 10th percentiles between 1980 and 2000. Much of the widening of neighborhood unemployment distributions within the urban areas of the United States took place between 1980 and 1990, when the average 90th percentile increased while the 50th and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

[9] A list of the metropolitan areas in the sample appears in the appendix.

[10] 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.

Figure 2

Normalized Neighborhood Unemployment Percentiles



Although doing so does not influence the magnitudes of the percentile differences, it is also worthwhile to examine the evolution of each unemployment percentile after controlling for each metropolitan area's overall unemployment rate. That is, Figure 1 may be somewhat difficult to interpret because the percentiles may be higher (or lower) in one year than another simply because overall rates of unemployment have risen (or fallen). As an alternative, I calculate a set of "normalized" percentiles by taking the deviations of each metro area's percentiles from its overall rate of unemployment. That is, instead of reporting the three raw percentiles, I report each percentile minus the unemployment rate for the entire metropolitan area. The averages of these normalized percentiles appear in Figure 2. What they show, of course, is very much the same pattern: an increase in the rate of unemployment among neighborhoods with already high levels of unemployment and a decrease among neighborhoods with already low levels.[11]

[11] The normalized 90th, 50th, and 10th percentiles were 0.042, –0.004, and –0.031, respectively, in 1980. In 2000, they were 0.066, –0.009, and –0.046.

SOME POSSIBLE EXPLANATIONS

What might account for the increase in the geographic concentration of unemployment? This section considers three straightforward hypotheses 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 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 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 choose to 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 the residents of historical city centers will be able to locate and maintain a job.

Although somewhat mixed, the evidence does provide some support for this idea. 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), is strongly, positively associated with the employment rate of black workers. These workers, on average, represent large fractions of central-city dwellers. Ihlanfeldt and 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.

Quantifying sprawl, however, tends to be somewhat difficult because the term does not have a precise definition. There are, of course, a variety of measures that attempt to capture the basic concept that individuals and employers move 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).

In this paper, I quantify urban decentralization within a metropolitan area using population density, which is constructed as a weighted average of neighborhood-level densities. The weights in this case are given by each neighborhood's share of total metropolitan area population. Hence, a metropolitan area's density is taken to be the density of the neighborhood 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.[12]

Summary statistics describing levels of population density among the 361 metropolitan areas in the sample in each year appear in Table 2. Between 1980 and 2000, the average metropolitan area saw its density decrease from 3,080 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 in two decades earlier.[13] This pattern is generally consistent with the long-standing trend for U.S. populations to spread out geographically.

Industrial Shifts and Unionization

The past 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, rates of unionization have fallen substantially.

Some of these changes can be seen in the summary statistics reported in Table 2. 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. Rates of unionization 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 con-

[12] 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).

[13] 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.

Table 2

Summary Statistics: Unemployment Covariates

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
	% FIRE	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
	% FIRE	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
	% FIRE	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. "FIRE" is the financial, insurance, and real estate sector.

centrated among the residents of certain neighborhoods, these changes may have produced differential rates of unemployment across different areas within a city. In other words, rather than a change occurring in the way residents of a metropolitan area sort themselves across neighborhoods (e.g., into areas populated primarily by either high-skill or low-skill workers), it may simply be that changes in the labor market have affected workers in different neighborhoods in different ways.

Segregation by Income and Education

The increase in concentration of unemployment may, on the other hand, be the product of greater segregation of individuals by income and education. If the manner by which individuals sort themselves into residential areas has created neighborhoods with concentrations of either high- or low-skill individuals, we should see 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.[14]

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 (e.g., Glaeser and Kahn, 2004). Recent work, however, challenges this view. In particular, Wheeler (2006) finds little association between the extent to which urban populations spread out and the income differentials they exhibit across either neighborhoods or tracts.

To quantify income segregation, I compute the extent of variation between neighborhoods as follows:

$$\text{(2)} \qquad \textit{Income Variation} = \sum_{i=1}^{N} \omega_i \left(\bar{y}_i - \bar{y}\right)^2,$$

where $\bar{y}_i$ is the average household income of neighborhood i, $\bar{y}$ is the average household income in the city, ω_i is the share of the metropolitan area's households living in neighborhood 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, I compute an index of dissimilarity for college graduates.[15] Recall, the resulting values represent the fraction of a city's population with a bachelor's degree or more that would have to relocate for these individuals to be uniformly distributed throughout the city.

Summary statistics describing the evolution of these two segregation measures appear in Table 2. 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 decade of 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.

EMPIRICAL ANALYSIS

Specification and Primary Results

To test the hypotheses outlined here, I consider 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:

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

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.

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

[15] 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.

Table 3

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)
% FIRE	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^2	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 U.S. Census region indicators; * indicates significance at the 10 percent level or better. "FIRE" is the financial, insurance, and real estate sector.

The vector of characteristics, X_{ct}, includes the following: log population density; the proportions of the city's resident population that are (i) female, (ii) black, (iii) foreign-born, (iv) under the age of 24, and (v) over the age of 65; the share of total employment in each of nine broad sectors; the city's overall unemployment rate; the proportion 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.[16] I also include three region dummies that are interacted with the year indicators, δ_t.

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. In addition, some neighborhoods may be more sensitive to changes in the local business cycle than others. Hence, the unemployment rate and the six region-year interactions are included

[16] The nine industries are manufacturing; agriculture, forestry, fisheries; construction; wholesale trade; retail trade; finance, insurance, real estate; public administration; education services; and health services. Because of 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.

to control for the influence of fluctuations in local and regional economic activity.

The remaining covariates are included to assess the hypotheses sketched above. 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 neighborhoods.

Estimation of equation (3) is accomplished using the within-estimator, whereby all variables are expressed as deviations from averages taken within metropolitan areas. The parameters are then estimated by ordinary least squares. The results appear in Table 3. 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, for example, 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, hence, a low incidence of unemployment among all individuals. It could also be a reflection of 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. 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 supports the hypothesis sketched in the section "Industrial Shifts and Unionization." In particular, the decline of manufacturing and 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 3, 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, likely to be some endogeneity associated with the income segregation variable. After all, as the distribution of unemployed households becomes more uneven within a metropolitan area, the distribution of income will very likely become more uneven, too, because income tends to be strongly tied to employment status. As a result, the coefficient on income segregation likely exhibits some upward bias. 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. This suggests that any bias in the estimated coefficient on the education dissimilarity index may be small.

The estimates in the next three columns of Table 3, 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 3 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 the trends in neighborhood-level unemployment.

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 neighborhoods may be extremely small, possessing only a few households, the majority of whom happen to be unemployed. These neighborhoods 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 neighborhoods with smaller numbers of employed and unemployed individuals. Hence, an extremely small neighborhood 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, I examine weighted percentiles, where the weights are given by the size of each neighborhood's labor force. After computing these percentiles, I simply create 90-10, 90-50, and 50-10 differences and estimate the same regressions as those reported in Table 3.

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 0.069, 0.044, and 0.026, respectively, in 1980. By 2000, they had risen to 0.096, 0.065, and 0.031.

The regression results for these weighted differentials are presented in Table 4. 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 neighborhoods 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.

Table 4

Robustness-Weighted Percentile Difference

	Dependent variable		
Regressor	Weighted 90-10 difference	Weighted 90-50 difference	Weighted 50-10 difference
% College	–0.13* (0.04)	–0.07* (0.04)	–0.06* (0.02)
% Female	0.09 (0.09)	0.14 (0.1)	–0.05 (0.05)
% Black	0.004 (0.05)	0.05 (0.05)	–0.04* (0.03)
% Under 24	0.05 (0.05)	0.07 (0.05)	–0.02 (0.03)
% Over 65	0.06 (0.07)	0.03 (0.07)	0.02 (0.03)
% Foreign-born	–0.02 (0.03)	–0.04 (0.03)	0.02 (0.02)
% Manufacturing	0.007 (0.04)	–0.005 (0.03)	0.01 (0.02)
% Agriculture, forestry, fisheries	0.05 (0.06)	0.009 (0.06)	0.04 (0.03)
% Construction	0.02 (0.07)	–0.006 (0.07)	0.02 (0.03)
% Wholesale trade	–0.015 (0.09)	0.000004 (0.08)	–0.01 (0.04)
% Retail trade	0.06 (0.05)	0.04 (0.05)	0.02 (0.03)
% FIRE	–0.07 (0.08)	–0.01 (0.08)	–0.06 (0.04)
% Public administration	–0.007 (0.06)	0.006 (0.06)	–0.01 (0.03)
% Education services	0.07 (0.07)	0.001 (0.07)	0.07* (0.03)
% Health services	0.16* (0.07)	0.14* (0.07)	0.02 (0.03)
Unemployment rate	0.94* (0.05)	0.63* (0.04)	0.3* (0.02)
Unionization rate	–0.01 (0.03)	–0.02 (0.03)	0.006 (0.01)
Education segregation	0.09* (0.02)	0.04* (0.02)	0.05* (0.01)
Income segregation	0.13* (0.03)	0.11* (0.03)	0.02* (0.01)
Log population density	0.01* (0.005)	0.008* (0.004)	0.003 (0.002)
R^2	0.78	0.65	0.55

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 U.S. Census region indicators; * indicates significance at the 10 percent level or better. "FIRE" is the financial, insurance, and real estate sector.

CONCLUSION

This paper has documented a rise in the extent to which unemployed households throughout 361 U.S. metropolitan areas have become concentrated residentially. In 1980, the median unemployed worker resided in a neighborhood with an unemployment rate of 7.5 percent; by 2000, that rate was 7.9 percent. Again, this is particularly striking in light of the fact that, 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 between three percentiles (either weighted or unweighted) of the neighborhood unemployment distribution—show similar qualitative trends. Hence, 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, I find 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 in the introduction, 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: (i) rising inequality in both income and earnings and (ii) an increase in the expected duration of unemployment. Both are 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).[17] 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 those within the same group. Although there has not been a long-run trend in the overall rate of unemployment, Abraham and Shimer (2001) report 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 what they call "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 very likely related to skill-biased technological change, changes in the institutional makeup of the labor market (e.g., declining union activity and minimum wage changes), 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 that Topa (2001) finds 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 employers simply avoiding workers from high-unemployment neighborhoods due to a social stigma. 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.

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

REFERENCES

Aaronson, Stephanie; Fallick, Bruce; Figura, Andrew; Pingle, Jonathan and Wascher, William. "The Recent Decline in the Labor Force Participation Rate and Its Implications for Potential Labor Supply." *Brookings Papers on Economic Activity*, 2006, I, pp. 69-134.

Abraham, Katharine G. and Shimer, Robert. "Changes in Unemployment Duration and Labor Force Attachment." NBER Working Paper 8513, National Bureau of Economic Research, October 2001.

Acemoglu, Daron. "Technical Change, Inequality, and the Labor Market." *Journal of Economic Literature*, March 2002, *40*(1), pp. 7-72.

Benabou, Roland. "Workings of a City: Location, Education, and Production." *Quarterly Journal of Economics*, August 1993, *108*(3), pp. 619-52.

Case, Anne C. and Katz, Lawrence F. "The Company You Keep: The Effects of Family and Neighborhood on Disadvantaged Youths." NBER Working Paper 3705, National Bureau of Economic Research, May 1991.

Cutler, David M.; Glaeser, Edward L. and Vigdor, Jacob L. "The Rise and Decline of the American Ghetto." *Journal of Political Economy*, June 1999, *107*(3), pp. 455-506.

Glaeser, Edward and Kahn, Matthew. "Sprawl and Urban Growth," in J. Vernon Henderson and Jacques-Francois Thisse, eds., *Handbook of Regional and Urban Economics.* Volume 4. Amsterdam: Elsevier, 2004, pp. 2481-527.

Hirsch, Barry T.; Macpherson, David A. and Vroman, Wayne G. "Estimates of Union Density by State." *Monthly Labor Review*, July 2001, *124*(7), pp. 51-55.

Hobbs, Frank and Stoops, Nicole. "Demographic Trends in the 20th Century." U.S. Census Bureau, Census 2000 Special Reports, Series CENSR-4. Washington, DC: U.S. Government Printing Office, November 2002.

Ihlanfeldt, Keith R. and Sjoquist, David L. "The Impact of Job Decentralization on the Economic Welfare of Central City Blacks." *Journal of Urban Economics*, July 1989, *26*(1), pp. 110-30.

Juhn, Chinhui; Murphy, Kevin M. and Pierce, Brooks. "Wage Inequality and the Rise in Returns to Skill." *Journal of Political Economy*, June 1993, *101*(3), pp. 410-42.

Kain, John F. "Housing Segregation, Negro Employment, and Metropolitan Decentralization." *Quarterly Journal of Economics*, May 1968, *82*(2), pp. 175-97.

Katz, Lawrence F. and Murphy, Kevin M. "Changes in Relative Wages, 1963-1987: Supply and Demand Factors." *Quarterly Journal of Economics*, February 1992, *107*(1), pp. 35-78.

Levy, Frank and Murnane, Richard J. "U.S. Earnings Levels and Earnings Inequality: A Review of Recent Trends and Proposed Explanations." *Journal of Economic Literature*, September 1992, *30*(3), pp. 1333-81.

Topa, Giorgio. "Social Interactions, Local Spillovers and Unemployment." *Review of Economic Studies*, April 2001, *68*(2), pp. 261-95.

Weinberg, Bruce A. "Black Residential Centralization and the Spatial Mismatch Hypothesis." *Journal of Urban Economics*, July 2000, *48*(1), pp. 110-34.

Wheeler, Christopher H. "Urban Decentralization and Income Inequality: Is Sprawl Associated with Rising Income Segregation Across Neighborhoods?" Working Paper No. 2006-037A, Federal Reserve Bank of St. Louis, 2006.

Wilson, William J. *The Truly Disadvantaged: The Inner City, The Underclass, and Public Policy.* Chicago: University of Chicago Press, 1987.

APPENDIX

Metropolitan Areas

Abilene, TX
Akron, OH
Albany, GA
Albany-Schenectady-Troy, NY
Albuquerque, NM
Alexandria, LA
All MSAs
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