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Abstract

A well-known challenge is measuring employment concentration across metropolitan areas and analyzing the evolving spatial structure. We introduce a new approach that avoids identifying "job centers" and conceptualizes the distribution of employment based on two dimensions: 1) employment deconcentration and 2) spatial dispersion of high employment locations. We apply this framework to study 329 US metropolitan regions based on 1 sq km. grid cells. We find diverse trajectories of metropolitan restructuring between 2000 and 2010, and substantial variation across regions in employment concentration. The new framework enables researchers to compare metropolitan regions to gain insights into the dynamic nature of metropolitan spatial structure.

Keywords: metropolitan regions; employment deconcentration; urban scale

Bios

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Proposing New Measures of Employment Deconcentration and Spatial Dispersion across Metropolitan Areas in the U.S.

The historical development of cities is a key distinguishing feature of modern society, and given the importance of employment for the generation of cities, scholars have naturally paid particular attention to the spatial layout of businesses in cities. A feature predominant in early studies influenced by von Thunen's work (1826) was that cities tended to exhibit a monocentric pattern in which the vast majority of firms (and thus jobs) were located in a central business district (CBD), with residences built in the areas surrounding this CBD (see e.g., Alonso 1964; Mills 1967; Muth 1969). As time has gone by, and the size of cities has increased tremendously, a body of scholarship has focused on the question of whether this degree of concentration of employment has remained. In this literature, the question often raised is whether the monocentric nature of cities remains, or whether beyond a particular size cities transition into polycentric areas, or even more recently the idea of scatteration (Salvati, Venanzoni, Serra, and Carlucci 2016) in which there are not simply a few discrete job centers, but rather that employment is located more extensively across the spatial area. At root in many of these discussions, we argue, are the questions of 1) the *degree of deconcentration* of employment in regions, and 2) the *degree of spatial dispersion of employment*.

This literature studying the degree of concentration of employment has often adopted the strategy of determining the presence of employment subcenters in metropolitan areas, and, while undoubtedly valuable, this task has resulted in definitional and methodological uncertainty that has raised challenges for this research. There is a growing awareness that the definition and measurement of employment subcenters not only varies across studies, but furthermore there are many possible definitions and operationalizations of the concept (Gardner and Marlay 2013; Hajrasouliha and Hamidi 2017). Particularly troubling is the evidence that analytic results can differ considerably depending on which definition or technique is utilized (Hajrasouliha and Hamidi 2017).

This uncertainty is particularly concerning given that it is therefore unclear how we can evaluate the results that are obtained when comparing the number (or other characteristics) of employment subcenters across metropolitan areas. A more complete understanding of the nature of employment deconcentration in contemporary metropolitan areas may require a systematic comparison of metropolises using metrics or methods that can be consistently applied to a diverse group of metropolitan areas and examination of interregional variations and their contributors. Whereas the value of case studies should not be underestimated, it is also crucial to investigate how the concentration of economic activities has changed over time in different regions having different initial conditions, growth trajectories, industrial structures, and demographic compositions. By doing so, one could test if a certain principle exists regarding the distribution of employment, as hinted at by some recent studies seeking universal laws of urban growth and transformation (Arribas-Bel, Ramos, and Sanz-Gracia 2015; Bettencourt, Lobo, Helbing, Kühnert, and West 2007; Bettencourt, Lobo, Strumsky, and West 2010; Huang and Yost-Bremm 2018).

In this article, therefore, we provide a new approach and demonstrate its usefulness in understanding the complex spatial structure of contemporary metropolises and its change over time. The new approach focuses on 1) the level of *employment deconcentration*, and 2) the level of *spatial dispersion* (rather than attempting to identify employment (sub)centers). We apply the new approach to an analysis of 329 United States metropolitan statistical areas (MSAs) to demonstrate how this two dimensional approach can enhance our understanding of metropolitan spatial structure, while minimizing methodological arbitrariness. This approach avoids any uncertainty about defining subcenters, and allows researchers to directly compare the level of concentration and dispersion across MSAs. Another advantage of the strategy is that it is straightforward to measure employment deconcentration and spatial dispersion over time, making longitudinal comparisons far easier than comparisons based on employment subcenters whose boundaries can shift over time.

Measuring employment deconcentration and understanding metropolitan spatial structure

Previous research

There is a longstanding interest in the degree of employment concentration in metropolitan areas. Given that early scholars observed that cities initially exhibited a monocentric form in which there was a downtown business district surrounded by residential areas (Alonso 1964; Mills 1967; Muth 1969), much subsequent research has attempted to measure not only the central business district, but also other business subareas in a region (Giuliano and Small 1991; McDonald 1987; McMillen 2001; McMillen 2003). The identification of employment subcenters has enabled us to better understand the evolving spatial structure of contemporary metropolises and their workings over the last several decades (Arribas-Bel, Ramos, and Sanz-Gracia 2015; Giuliano, Redfearn, Agarwal, Li, and Zhuang 2007; McMillen and Lester 2003).

However, a growing number of scholars have noted recently the methodological challenges that arise in defining and measuring employment subcenters (see e.g., Gardner and Marlay 2013; Hajrasouliha and Hamidi 2017; Lee 2007; McMillen 2001; Redfearn 2007). A fundamental problem is that there is no single agreed upon definition, and the various strategies that exist can differ considerably. The most popular strategies, which use (gross) employment density and total employment as two main criteria, require various cutoff values (for both employment density and total employment) be specified, and these are somewhat arbitrary with little external justification other than following precedent in the literature or local knowledge. Given that this literature rests upon the theoretical foundation of the notion of agglomeration economies, one would presume it better to make such decisions based on evidence of how agglomeration in fact plays out at the level of businesses. However, such evidence is typically not reducible to a single rule, resulting in the indeterminacy this literature encounters.

Another challenge is defining the base units of analysis that are then potentially aggregated into subcenters: some research has used units such as census tracts (Arribas-Bel, Ramos, and Sanz-Gracia 2015; Gordon, Richardson, and Wong 1986; Huang and Yost-Bremm 2018) or block groups (Hajrasouliha and Hamidi 2017), although some scholars argue that tracts are too large and therefore can be heterogeneous in that one part of a tract may belong in an employment subcenter whereas another part is simply residential. Therefore more recent studies have used smaller units such as grid cells (e.g., 1km×1km cells) as the base units (Kane, Hipp, and Kim 2018; Krehl and Siedentop 2018). Certainly, smaller units are preferred in order to increase the plausibility of the assumption of homogeneity of business patterns within units, but smaller units can result in data and computational challenges.

An associated issue is defining contiguity of the smaller units that might be combined into the subcenter: should this be based on queen contiguity, rook contiguity, distance contiguity, or some other such definition? There is no correct answer, and the results can differ based on this choice as well. For example, if one uses a grid for the smaller units, and then uses queen contiguity for defining adjacency, the result can be a subcenter that looks like the path of a Bishop in a game of chess, which is not typically what one envisions when considering a subcenter (which typically is thought of in a more compact, rectangular form). If one instead requires rook contiguity, the resulting subcenters will be different than those obtained using queen contiguity, again emphasizing the uncertainty of the subcenters approach.

Because of these various uncertainties in the definition and operationalization of subcenters, some research has instead employed relative comparisons for determining subcenters. One such approach uses spatial statistics, which enables researchers to identify subcenters in a less restrictive manner (McMillen 2001; Redfearn 2007). For example, one stragegy uses Local Indicators of Spatial Association (LISA) statistics to define subcenters with a focus on the extent to which the number of jobs in clusters of cells/tracts are much higher than surrounding areas or spatially-varying thresholds determined from the data of the region (Krehl and Siedentop 2018; Riguelle, Thomas, and Verhetsel 2007; Salvati, Venanzoni, Serra, and Carlucci 2016). Another strategy uses nonparametric regression to capture local peaks in the distribution of jobs across a metropolitan area (McMillen 2001; Redfearn 2007). Despite their flexibility, these approaches nonetheless require decisions about the geographic scope of surrounding areas (e.g., band width). Another consequence of these relative approaches is that a subcenter can be defined at a location that has only a moderate number of jobs—but has notably more jobs than in the surrounding areas that have almost no jobs—and yet have fewer jobs than other (more central) locations within the MSA that are not defined as part of a subcenter based on the band width adopted due to relatively higher levels of job density in the nearby areas.

Recognizing these challenges, recent studies have attempted to better capture and analyze variations in employment concentration in various ways. While some studies, such as Arribas-

Employment deconcentration in MSAs

Bel and Sanz-Gracia (2014) and Hajrasouliha and Hamidi (2017), have sought a better appraoch to identifying employment centers using local indicators of spatial clustering, others have avoided focusing on employment centers in their analysis of metropolitan spatial structure. Yao and Kim (2017), for instance, employed standard deviation elipeses to measure the degree to which jobs are decentralized in each of the largest US metropolitan areas with more than 500,000 commuters. Also, although the focus is not specifically on employment concentration, there is a body of research concerning the measurement of sprawl vs. compactness. “Starting around 2000, researchers sought to develop objective measures of sprawl that could be related to measurable outcomes” (Hamidi, Ewing, Preuss, and Dodds 2015: p. 36), and studies in this literature often construct several indices to capture the multidimensionality of sprawl. For example, one study constructed four dimensions of metropolitan urban form: metropolitan size, activity intensity, the degree that activities are evenly distributed, and the extent that high-density sub-areas are clustered (based on the global Moran’s I coefficient) (Tsai 2005). Yet another study combined seven dimensions for measuring sprawl, including density, continuity, concentration, centrality, proximity, mixed use, and nuclearity (Cutsinger and Galster 2013). A more recent study also constructed four dimensions through which sprawl can be distinguished from compact development: 1) density; 2) mix use; 3) activity centering; 4) street (Hamidi, Ewing, Preuss, and Dodds 2015). In this study, density was based on both population and employment, and the other dimensions considered the mix of jobs and population in various manners, the accessibility of amenities, and the street connectivity. Thus, although measuring sprawl is clearly important, it is conceptually quite distinct from employment concentration specifically.

An alternative strategy: New proposed measures of employment deconcentration and spatial dispersion

Employment deconcentration in MSAs

Given all these challenges with defining and measuring employment subcenters, we propose employing a more straightforward approach to measuring the distribution of employment in a metropolitan region with fine scale data in order to better understand the complexity and dynamics of contemporary metropolitan spatial structure rather than attempting to identify subcenters. This does not mean that subcenter-oriented thinking or analysis does not provide any value-added. It is hard to deny that employment (sub)centers can have significant implications for the working of a metropolitan system as often revealed in development densities, housing prices, and commuting flows. However, an alternative strategy for quantifying employment distribution is warranted in the circumstances (e.g., cross-sectional or panel analysis with a large number of metropolitan regions) where subcenter identification is likely to suffer from the aforementioned challenges.

Our proposed strategy is to develop a two-dimensional framework that covers the degree of employment deconcentration and spatial dispersion in metropolitan areas, which we think are questions of particular substantive interest (Figure 1). For the first dimension (i.e., Employment Deconcentration), we employ a measurement strategy which is based on the insights of the criminology literature that in recent years has focused on the question of the degree of crime concentration (Andresen, Curman, and Linning 2016; Bernasco and Steenbeek 2016; Braga and Clarke 2014; Groff, Weisburd, and Yang 2010; Hipp and Kim 2017; Levin, Rosenfeld, and Deckard 2016; Weisburd 2015). Specifically, we adopt an approach measuring the degree of deconcentration by determining the minimum required land areas (in percentage terms) to account for a certain share of the total employment, say 50%. This approach provides a value – for instance 10%, if 50% of the total jobs are concentrated within the top 10% of high employment cells in the region – that can be readily used to discern varying levels of employment deconcentration.

<<<Figure 1 about here>>>

This criminology literature was particularly energized by the notion that perhaps a "law" of crime concentration exists in which the degree of crime concentration is relatively similar across various cities (Weisburd 2015). Although there are various challenges for this literature as far as comparing the observed degree of concentration to what would be expected randomly (Eck, Lee, O, and Martinez 2017; Hipp and Kim 2017), such is not a concern here for employment deconcentration since we are mainly interested in comparing the relative level of concentration across these cities rather than an absolute value. Furthermore, a challenge in the criminology literature that occurs when the number of crime incidents is less than the number of geographic units is not an issue here since the number of jobs is far greater than the number of grid cells we measure in each metropolitan area (Bernasco and Steenbeek 2016).

To standardize comparisons across metropolitan areas, we adopt an approach that first creates one square kilometer grid cells in the urbanized areas across the entire U.S., and then within each MSA we compute the degree of employment deconcentration (ED).[1] To detect a measure of the percent of jobs in high employment (HE) grid cells we adopt the following approach. For ordered (greatest to least) job counts y_i in small geographic units i = 1, … I in a metropolitan area:

(1) $$HE(p) = \frac{\sum_{i=1}^{\tau} y_i}{\sum_{i=1}^{I} y_i}$$

(1a) $$ED = \frac{\tau}{I} * 100$$

[1] Note that our strategy generalizes to other possible subunits that might be used. For example, the researcher could use blocks, tracts, or other sized grid cells as the subunits.

where $HE(p)$ is the desired value of employment concentration: e.g., if 50% of employment is desired, then the value of τ that captures 50% of the total number of jobs is determined. The employment deconcentration (ED) value is therefore τ/I (the percent of cells that contain these jobs). Likewise $HE(p)$ can be defined as other values, such as 60%, 70%, etc. An alternative strategy defines $p = \tau/I$ as the fraction of concentration desired based on the percentage of cells: i.e., the percent of jobs contained in the top 5% of cells. We prefer our approach as it allows for a more straightforward construction of spatial dispersion, as we describe next.[2] One example using an analogous approach split census tract data for six metropolitan areas into quintiles based on employment and descriptively explored the changes over a decade (Lee 2007).[3]

Beyond the importance of the degree of general deconcentration of employment in a metro area is the question of the degree of *spatial dispersion* of those jobs (i.e., the second dimension of our proposed framework – Figure 1). For this important aspect of metropolitan spatial structure, our strategy selects the high employment (HE) cells defined in equation 1 and then measure how far these job-rich cells are from one another as a measure of spatial dispersion. This avoids the challenge of attempting to define subcenters, and instead computes a continuous measure of spatial dispersion that can be used to compare across metro areas.

[2] Although this alternative strategy yields similar results to our approach, it is unsatisfactory for measuring spatial dispersion. This is because our approach will result in fewer cells if jobs are more concentrated in an MSA, and therefore the average distance between these cells provides a more appropriate measure of distance. This alternative approach would compute the average distance of, say, the top 1% of grid cells, but fail to account for the fact that the top 1% of cells in one MSA could include a far higher percentage of jobs than those in another MSA.

[3] Our approach is comparable to what researchers have done in calculating the Gini coefficient to capture the uneven distribution of population or employment in studies on metropolitan spatial structure, such as Gordon et al. (Gordon, Richardson, and Wong 1986) and Tsai (2005). However, here, we make no attempt to collapse these percentages (in the top 1%, …, the bottom 1%) into a single index, as done in the formulation of the Gini coefficient or its derivatives, such as the Wright coefficient. We do this for two reasons. First, we argue that the fact of possible varying levels of employment deconcentration at different scales is of theoretical and substantive interest, since we can make a distinction between the amount of concentration in a very small percentage of MSA units (i.e., the top 50% of jobs) versus the amount of employment deconcentration in a broader percentage of the MSA (i.e., the top 80% of jobs). Second, our approach translates more readily to a measure of spatial dispersion of these jobs compared to using the Gini.

More specifically, we first compute the pairwise distance between these high employment cells and then calculate the average of these pairwise distances weighted by the number of jobs in each of the cells (DHE). We define job counts y_i in a small geographic unit i = 1, … τ, in which τ is the number of high employment cells in a metropolitan area from equation 1 earlier, and job counts y_i in another small geographic unit j = 1, … τ, with dist_{ij} capturing the distance between the two high employment cells:

(2) $$DHE = \sum_{i=1}^{\tau} \sum_{j=1}^{\tau} dist_{ij} \times (y_i \times y_j) \,/\, \sum_{i=1}^{\tau} \sum_{j=1}^{\tau} (y_i \times y_j)$$

By multiplying y_i and y_j together, we are obtaining pairwise distance between every set of jobs in the high employment cells in the region. This weighting procedure gives us an estimate of the average distance between any given job in these high concentration cells and all other jobs in high concentration cells. If we did not weight by the number of jobs, we would fail to capture how the number of jobs in cells impact this spatial distribution, as we demonstrate shortly.

We next standardize this measure given that there will likely be trivially shorter distances between high concentration grid cells in very small regions compared to very large regions. For the standardization, we compute the average distance between *every* grid cell in a region (DA):

(3) $$DA = \sum_{i=1}^{I} \sum_{j=1}^{J} dist_{ij} \times (y_i \times y_j) / \sum_{i=1}^{I} \sum_{j=1}^{J} (y_i \times y_j)$$

here we are using all grid cells in a metropolitan area, and therefore i = 1, … I in a metropolitan area and j = 1, … J in a metropolitan area.

We then compute the ratio of the average distance between the high employment cells and the average distance of all grid cells in a metropolitan area as the measure of spatial dispersion (SD):

(4) $$SD = DHE/DA$$

where DHE and DA come from equations 2 and 3, respectively. Smaller values indicate greater spatial concentration, whereas values greater than 1 indicate less spatial clustering compared to that expected by chance. Our ratio measure has an intuitive interpretation, as multiplying it by 100 provides the percentage of average distance between high concentration cells compared to the average distance of all cells in the region.

In sum, the proposed approach employs two measures that operationalize non-spatial and spatial aspects of the construct of interest: one is nonspatial and therefore only captures the degree to which a high number of jobs for an MSA are contained in a small number of grid cells, and the other is spatial and captures the average distance between these high concentration cells. This two-dimensional framework is expected to enable researchers to capture various possible directions of structural changes as well as their magnitudes. Note that conceptually a point on the lower left of Figure 1 indicates something approximating the monocentric city, as such cities have low levels of employment deconcentration in general, as well as low spatial dispersion (and hence low values on each of these measures). Such monocentric regions can undergo various pathways of transformation towards a more decentralized state, as illustrated in the figure. A question of interest is where contemporary metropolitan regions tend to be located on this coordinate system. An additional interesting question is how MSAs have transformed in recent years which can be captured as a transition from one point to another on the coordinate system.

Demonstrating the measures

Before we present an empirical application of the new framework and show how US metropolitan areas have been decentralized over the last decade, in this section, we demonstrate how our measures of employment deconcentration and spatial dispersion operate on a set of stylized examples. These examples are built on a hypothetical region with a 10x10 grid of cells, as shown in Figure 2. The number of jobs in a grid cell is shown (cells with no values shown have 2 jobs). Based on our deconcentration measure of the percentage of cells that contain 50% of jobs, city 1 has a value of 2% (as the two cells have 196 jobs, and the other 98 cells have the other 196 jobs). Cities 2-6 all have deconcentration values of 5%, as a minimum of 5 of the cells are required to contain 50% of the jobs. Cities 7 and 8 have deconcentration values of 10%. There are also varying degrees of spatial patterning that our spatial dispersion measure captures, as we describe next.

<<<Figure 2 about here>>>

These hypothetical cities tend to have more spatial dispersion going from city 1 to city 8. City 1 has a very small spatial dispersion ratio of 9.7% (so it is very spatially concentrated), as the two cells at the center contain half of the jobs. Given that in each of these two cells the 98 jobs have a distance of zero to the other jobs in the same cell, and a distance of .69 miles to the 98 jobs in the adjacent cell, the average distance between jobs in these high concentration cells is 0.345.[4] The average distance of all cells in this grid is 3.576 (based on distance), and therefore this yields a value of 9.7% (.345*100 / 3.576). Cities 2 and 3 both have deconcentration values of 5%, but whereas city 2 has a spatial dispersion value of 28.7%, city 3 has a much higher value of 57.1% (capturing the fact that the employment concentration is more spread out). The spatial difference between cities 3 and 4 is instructive: the high concentration cells themselves are in identical locations, but city 4 contains more jobs in the grid cells further from the center. Thus, city 4 has a spatial dispersion value of 61.5%, which is higher than city 3's value of 57.1%. Notably, our job-weighted measure captures this distinction: if we instead simply computed the

[4] We defined the distance between adjacent cells based on rook criterion to be .69 mile. The results, of course, generalize to any linear transformation of this value.

average distance between these high concentration cells (rather than weighting them by jobs), these two cities would have identical 63.5% spatial dispersion values.

City 5 is similar to city 3, except that the two cells with 35 jobs are a bit further away from the center, and this is captured by our measure as the spatial dispersion for this city is 65.3% (compared to 57.1% for city 3). City 6 has fewer jobs in the center grid cell, but more in the further away cells, and thus has an even higher spatial dispersion value of 69.6%. City 7 is an interesting case, as it has more job deconcentration compared to city 6 (10% vs. 5%), but has nearly identical spatial dispersion (69.8% vs. 69.6%). The relative closeness of these cells to one another in city 7 (as pairs of high concentration cells are adjacent), explains why it can have a similar spatial dispersion as city 6. City 8 demonstrates a case where the low concentration is accompanied by cells that are not adjacent, and therefore it has the most spatial dispersion of the hypothetical cities (79.2%). Thus, these stylized cities demonstrate that our measures operate in the desired fashion. We next turn to our empirical analyses.

An Application to US Metropolitan Areas

Data and Methods

In order to demonstrate how the new measurement strategy works in an empirical analysis setting and what additional insights can be gained, we apply the two measures to 329 metropolitan areas in the U.S. using Reference USA Historical Business Data; these data provide the location of every business in the U.S. and the number of employees for each business establishment in 2000 and 2010 (Infogroup 2015). For this, we first created a grid of 1 sq. km. cells covering the entire conterminous U.S., based on a projection system for the large geographic extent. We then excluded grid cells that fell outside of any Urbanized Areas (UAs) using the 1999 UA boundary definition that would best fit our study time period. This procedure enabled us to remove large unpopulated areas that would otherwise be classified as part of metropolitan areas, and would bias our estimates of employment deconcentration and spatial dispersion.

After creating this grid, for businesses without latitude/longitude points we geocoded them and placed them at latitude/longitude points, and then aggregated all Reference USA business data points to the appropriate grid cell, and computed the total number of jobs in each grid cell in each of the 329 MSAs in the U.S. We then sorted the grid cells within each MSA by descending order of jobs for each of the 329 metropolitan areas. This allowed us to determine the minimum percentage of grid cells within an MSA that contain 50% of the jobs for our measure of employment deconcentration. We similarly computed the minimum percentage of grid cells containing 60%, 70%, and 80% of the total jobs in each region. As mentioned earlier, given the substantive interest in the level of concentration at various scales, we computed the degree of concentration among these various percentages of grid cells. We created these employment deconcentration measures in 2010. We also created a set of employment deconcentration measures in 2000, and computed the difference from 2000 to 2010 to capture change.

We also computed the value of our second measure (i.e., spatial dispersion) for each of the 329 MSAs using the high employment cells that account for 50%, 60%, 70%, and 80% of the total employment in the region. In doing so, as explained earlier, we used a weighting procedure (based on jobs) to take into account uneven distribution of employment in calculating the average distance between high concentration cells. Further, the calculated distance was standardized by the average distance between all cells in the region to create our measure of spatial dispersion.

Regarding this standardization, it is important to note that we assessed an alternative strategy that instead pulled 1,000 random samples of grid cells from the region with the number of cells equal to the number of high concentration cells in that metro area, and computed the average distance between cells in each random sample. We then assessed where our measure of average distance between high concentration cells falls within this random distribution of 1,000 average distances (what we term the *z-score approach*). However, we found that this strategy resulted in values that were heavily skewed towards large regions: the correlation between this measure and overall population of the region was about -.78.[5] Our preferred ratio approach has a correlation with population of about .03.

In the following section, using these two metric values, we will assess the degree of employment deconcentration and spatial dispersion across metro areas. Furthermore, we will demonstrate how our measures can be used to capture change over time based on employment change between 2000 and 2010.

General patterns of decentralization

We first describe the average values of our measures for the level of deconcentration and the spatial dispersion of all metropolitan areas. The results are displayed in Table 1, and show that the average deconcentration value for the top 50% of jobs across all 329 metropolitan areas in 2000 was 4%, with a standard deviation of 1.5%. Thus, on average, 4% of the grid cells in a

[5] This result is not terribly surprising, as a larger region will have a larger sample size of grid cells, and therefore this greater precision will make it appear that the observed distance between high concentration grid cells is further out on the distribution based on the z-score (due to the smaller standard deviation) compared to an MSA with fewer grid cells. One could adjust the z-score based on the number of grid cells, to adjust for this, but the resulting value arguably would not have an intuitive meaning. We therefore prefer our approach given that it yields an interpretable numeric value.

metropolitan area contain 50% of jobs in the metropolitan area. On average, 6.2% of the grid cells contain 60% of jobs in metropolitan areas, whereas 9.4% and 14.2% are required to cover 70% and 80% of jobs, respectively, in 2000. It appears deconcentration had increased by 2010, as the average comparable values for covering 50% to 80% of jobs were 4.8%, 7.4%, 11.1%, and 16.5%, respectively. Nonetheless, there was considerable variability across metropolitan areas in this deconcentration, and its change, as indicated by the standard deviation values for these measures.

<<<Table 1 about here>>>

The spatial dispersion measures also have a clear interpretation. In 2000, in the average metropolitan area the top 50% high concentration grid cells were 54.7% as far from each other as were all grid cells in the metropolitan area. The top 60% high concentration grid cells were 57.8% as far from each other as were all grid cells in the metropolitan area. The comparable values for the top 70% and top 80% of grid cells were 61.2% and 64%, respectively. By 2010 the mean values across these different spatial extents had all increased from 2000. Thus, we observe that spatial dispersion across all metropolitan areas increased, on average, although there was nonetheless considerable variability given the relatively large standard deviation of these changes (the last row in Table 1).

Interregional variation

We next describe our measures for the 40 largest metropolitan areas based on population to demonstrate how this approach captures interregional variation. Table 2 shows the values (and z-scores across all 329 metropolitan areas to give a sense of the magnitudes) for these large metropolitan areas for the deconcentration and spatial dispersion measures based on the top 50% of jobs in 2000, in 2010, and the change over the decade. We see that the New York MSA has the least deconcentration at both time points among these large metropolitan areas, as just 1.6% and 1.5% of grid cells are needed to capture 50% of jobs in 2000 and 2010, respectively (z-scores of -1.6 and -2.11). Consistent with what we know of New York, it also has very low spatial dispersion, as the high concentration grid cells are 17.8% and 17.3% as far from each other as are all grid cells in the metro areas in 2000 and 2010, respectively (z-scores of -1.88 and -2.15). While New York experienced a decrease in deconcentration and spatial dispersion over the decade, the decrease in spatial dispersion was more modest (z-score = -0.19). For example, the Sacramento MSA experienced a much larger decrease in spatial dispersion over the decade, falling from 58.5% to 51.2%. Despite this decrease, Sacramento still has a fair amount of spatial dispersion; furthermore, it is much more deconcentrated than New York and experienced increasing deconcentration over the decade, rising from 4.6% to 6.2%.

<<<Table 2 about here>>>

At the other end of the spectrum, the MSAs of Orange County, CA and Fort Lauderdale, FL have some of the highest levels of deconcentration of any metropolitan areas. In Fort Lauderdale, fully 10.5% and 11.5% of grid cells are necessary to contain 50% of jobs in 2000 and 2010, respectively (for Orange County the values were 10% and 11%). Both of these metropolitan areas even experienced increasing deconcentration during this decade. And whereas Orange County has relatively high spatial dispersion as well, Fort Lauderdale has some of the highest levels of spatial dispersion of all metropolitan areas, as the high concentration grid cells are 77.1% and 83.6% as far from each other as are all grid cells in the metropolitan area. This high spatial dispersion in Fort Lauderdale is accompanied by a relatively large increase over the decade. Nonetheless, among these large metropolitan areas, both Columbus, OH and Seattle experienced even larger increases in spatial dispersion during the decade. Columbus' relatively high spatial dispersion increased from 57.4% to 66.1%, and Seattle's denser employment nonetheless rose from 42.3% to 50.7% during the decade. Whereas Seattle has relatively low spatial dispersion but experienced an increase during the decade, at the opposite end of the spectrum is Oakland, CA which has very high spatial dispersion (84.9% and 80.3% in 2000 and 2010), but nonetheless experienced a decrease during the decade.

These two measures of deconcentration and spatial dispersion sometimes move in tandem. Consider the metropolitan areas with the largest increase and decrease in deconcentration over this decade. On the one hand, Boston, MA experienced one of the largest decreases in deconcentration during the decade, falling from 3.5% to 3%, and also experienced a decrease in spatial dispersion (from 41.5% to 38.8%). At the other extreme, Las Vegas, NV had one of the largest increases in deconcentration, going from 3.3% to 5.2%, and also saw an increase in spatial dispersion (even if it was at a relatively low spatial dispersion to begin with), from 23.9% to 24.9%.

To demonstrate what some metropolitan areas look like with high or low values on our measures, and to show instances in which the deconcentration and spatial dispersion measures differ, in Figure 3 we present maps of four metropolitan areas in 2010. In these maps, we colored the number of jobs in high concentration grid cells by varying shades of blue, with the darkest blue indicating the most jobs. In the top left we show Sharon, PA, which is high on both deconcentration and spatial dispersion. The relatively large number of high employment cells demonstrates deconcentration, and the fact that they are scattered around the metropolitan area indicates spatial dispersion. Pueblo, CO in the bottom left is high in deconcentration but low in spatial dispersion. This can be seen in that there are a number of high employment cells, but they are still mostly located towards the center. Clarksville, TN in the top right is an example of a case with low deconcentration and high spatial dispersion. This combination appears to capture a polycentric area, as the low deconcentration is an indicator of job clustering, but the high spatial dispersion indicates that these clusters are well separated from one another. Finally, the bottom right map shows Bloomington, IN which is low in deconcentration and spatial dispersion. This appears to be the classic monocentric case, which is captured by the very few high employment cells that are concentrated in small areas.

<<<Figure 3 about here>>>

We also demonstrate how our measures can capture change over the decade by displaying maps of four metropolitan areas that exhibited distinct patterns of change in our measures from 2000-10 in Figure 4. In these maps, we colored the number of jobs in high concentration grid cells in 2000 by varying shades of yellow (the darkest yellow indicates cells with the most jobs in 2000), and in 2010 by varying shades of blue (the darkest blue indicates cells with the most jobs in 2010). Thus, cells present as high employment cells at both time points are varying shades of green (darker indicate more jobs at both time points). In the top left map, Laredo, TX demonstrates a metropolitan area that has seen a sharp increase in both deconcentration and spatial dispersion. Thus, the many more blue than yellow cells indicates the increase in deconcentration, and the fact that these blue cells tend to be farther away from the general clustering of the green and yellow cells indicates increasing spatial dispersion. Jersey City, NJ in the bottom left experienced increasing deconcentration but decreasing spatial dispersion. The increase in deconcentration is seen in the many more blue than yellow cells, but the fact that they tend to be centrally located close to the green cells captures the decreasing spatial dispersion. In contrast, Great Falls, MT in the top right map experienced decreasing deconcentration and increasing spatial dispersion, as seen by the fact that two yellow cells were replaced by a deep blue cell (more concentration) but this blue cell is far from the center (more spatial dispersion). Finally, Bloomington, IN in the bottom right map experienced decreases in both measures, and therefore the yellow cells are not replaced by any blue cells, and thus 2010 high employment is only in the two green cells.

<<<Figure 4 about here>>>

Comparing across deconcentration extent and spatial extent

Whereas we have been discussing the results for our measures based on the number of cells capturing the top 50% of jobs, we constructed similar measures for the top 60%, top 70%, and top 80% of jobs. We visually present these results for the largest 20 metropolitan areas in Figures 5a (employment deconcentration) and 5b (spatial dispersion). Figure 5a demonstrates that the measure, by design, requires a larger percentage of grid cells to capture systematically larger percentages of the total jobs in a metropolitan area. Nonetheless, the slopes of the lines need not be the same, and these differences indicate that the amount of deconcentration in a metropolitan area can differ based on the deconcentration extent employed. For example, whereas New York has the least employment deconcentration when measured capturing the top 50% of jobs (the bottom left of the graph) the consequence of their steeper line is that if we measure the deconcentration of the top 80% of jobs, New York has nearly caught Boston and Washington, DC (two lines on top of each other that are above New York). In contrast, whereas Riverside, CA has employment deconcentration at 50% jobs that is at the bottom of a large clump of metropolitan areas, the flatter line indicates that they have relatively less employment deconcentration at 80% jobs as the line is just above Boston and Washington, DC.

<<<Figures 5a and 5b about here>>>

Employment deconcentration in MSAs

Figure 5b displays the results of the spatial dispersion measures for the 20 largest metropolitan areas in 2010 at the different spatial extents. Note that for this measure there is not a monotonic necessity for the measure to increase for increasing spatial extent (as there is for the employment deconcentration measure). Although it is theoretically possible even for the values to be lower for larger percentages of jobs, we in general see a small increase in values when measuring the spatial distance between the high employment grid cells for an increasing percentage of jobs. Once again, we see differences in the slopes of the lines. For example, whereas Boston, MA has the second lowest spatial dispersion for 50% of jobs and Dallas, TX has the third lowest, their lines cross-over around the 60% job measure, and they have reversed places when measuring spatial dispersion among the top 80% of jobs. At 80% of jobs, Boston, MA has nearly the same spatial dispersion as Phoenix-Mesa, AZ, which exhibits a relatively flat spatial dispersion profile of values moving from 50% to 80%. Notably, Oakland, CA has very high spatial dispersion, as their high concentration cells are not much more clustered than chance given that the values between 80 and 90% are not much less than 100% (which is random).

Although we see some differences in the rankings of MSAs based on the deconcentration or spatial extent used, there are nonetheless considerable similarities across these measures when varying the extent values, suggesting that the sensitivity due to varying extents here is not as serious as that involved in subcenter-oriented methods. For example, in 2010 the correlations between the adjacent measures (i.e., 50% and 60%, 60% and 70%, 70% and 80%) are about .98. The correlations between measures 20% apart (i.e., 50% and 70%, 60% and 80%) are .95. And the correlation between the 50% and 80% measures is .90. Among the spatial dispersion measures, the correlations are also high, although a little lower: the correlations in 2010 between the adjacent measures are about .95, the correlations between measures 20% apart are .91, and the correlation between the 50% and 80% measures is .88. Despite these high correlations, some metropolitan areas have somewhat less similarity across spatial scale, as we just described in the differing slopes from Figures 5a and 5b. Why employment deconcentration or spatial dispersion might vary across spatial scales in some metropolitan areas would be a useful direction for future research; our measures provide a straightforward way to detect such locations.

Intertemporal change in employment deconcentration and spatial dispersion at different spatial extents

An advantageous feature of our continuous measures of employment deconcentration and spatial dispersion is that it is straightforward to measure change over time by creating difference measures over the decade. We graph out the change in our measures from 2000 to 2010 at these different deconcentration and spatial extents for the 20 largest MSAs in Figures 6a (employment deconcentration) and 6b (spatial dispersion). In Figure 6a we see that the change in employment deconcentration over the decade varies depending upon the extent used: whereas Phoenix-Mesa, AZ shows the largest increase regardless of extent, the much steeper line for it indicates that it has experienced particularly high increase in employment deconcentration when measured among the top 80% of jobs. In contrast, Boston, MA experienced a modest decrease over the decade that was of similar magnitude regardless of the spatial extent at which it was measured. There are differences in the slopes of the lines for various metro areas, which highlight the importance of extent for measuring employment deconcentration. As one example, Dallas, TX has experienced the second largest increase in employment deconcentration among these metro areas when measured as 80% of jobs, but it is in the middle of the pack of these metros when measured as 50% of jobs. This might point to the need to study Dallas more carefully as a case study.

Employment deconcentration in MSAs

<<<Figures 6a and 6b about here>>>

We show the change in spatial dispersion for the 20 largest metropolitan areas at different extents in Figure 6b. For the change in this measure, we see differences depending on the extent used. As one example, New York experienced the largest decrease in spatial dispersion among these metros when measured as 80% of jobs, but it experienced very little change when measured as 50% of jobs. As opposite examples, Oakland, CA and Boston, MA experienced the largest decreases in spatial dispersion when measured as 50% of jobs, but did not experience decreases when measured at the larger extents of 70% or 80% of jobs. Thus, whereas we saw relatively little differences in extent at a single point in time, or when measuring change in the employment deconcentration measure, it does appear that there can be differences in the change in spatial dispersion depending on the spatial extent at which this distance is measured.

Simultaneous intertemporal change in employment deconcentration and spatial dispersion

We also have the ability to observe how MSAs simultaneously change along both of our measures. In Figure 7 we plot the change along both of these measures for the 20 largest MSAs based on the top 50% of jobs. For example, we see in the top right that Orange County, CA (OC) not only has the highest employment deconcentration value of these large MSAs (being the highest MSA on the vertical extent in this figure) and a high spatial dispersion value (being towards the right side of this figure) but it increased along both dimensions during the 2000s (given that the arrow points upwards nearly 45 degrees). Just below it is Los Angeles (LA), which has mostly experienced increasing spatial dispersion, but little change in employment deconcentration (given that the arrow is less steep). Washington, D.C. (DC) has one of the lower employment deconcentration values (being towards the bottom of this figure) but experienced a large increase in spatial dispersion during the 2000s given the nearly horizontal arrow. New

York (NY) is notable in that it has the lowest values of employment deconcentration and spatial dispersion (and therefore is in the bottom left of the figure), and has shown effectively no change over the decade.

<<<Figure 7 about here>>>

Case studies: Phoenix and Columbus

We explored more closely two MSAs that exhibited particularly interesting patterns in Figure 7: Phoenix, AZ and Columbus, OH. In the case of Phoenix, the level of spatial dispersion remained relatively constant over the decade, however the level of employment deconcentration increased. Thus, in Figure 7 it is represented with an arrow pointing nearly straight up to capture these twin processes. However, whereas Columbus showed almost no change in employment deconcentration over the decade, the level of spatial dispersion increased. It is represented with an arrow pointing almost directly to the right in Figure 7 to capture these simultaneous processes. We demonstrated how these changes played out in these two MSAs in the maps of Figure 8 (Phoenix) and Figure 9 (Columbus). In these maps, we colored the number of jobs in high concentration grid cells in 2000 by varying shades of yellow and in 2010 by varying shades of blue, with the darkest shades indicating the most jobs. Therefore, cells present as high employment cells at both time points will be shaded green. We highlight specific changes that occurred in a few specific grid cells that help to understand these observed changes.

Figure 8 maps the Phoenix, AZ study area and shows a larger number of blue cells than that of yellow cells, indicating an increase in the degree of employment deconcentration (i.e., more cells required for the same percentage – 50% – of total employment in 2010, compared to 2000). A majority of these blue cells, however, are located in close proximity with existing job-rich areas, resulting in little change in terms of spatial dispersion. For instance, the red cell in the south of the city newly emerged in 2010, because it attracted large firms such as ADESA Auto Auctions, ALCAL Contracting, and Rotorway International Aircraft Manufacturing between 2000 and 2010. The other red cell, located in the west side of the city, represents the opening of the very large Banner Estrella Medical center in 2005, which increases the value of spatial dispersion given the more remote location (from 50.7% to 52%).

<<<Figure 8 about here>>>

The distribution pattern of blue cells is quite distinct in Columbus, OH (Figure 9). A considerable number of these cells, which represent newly emerging job-rich areas in the region, are located remotely, whereas many cells within the City of Columbus lost their jobs and thus are shown in yellow in the figure. For instance, the black cell near the center of the city was no longer included in the list of the region's job-rich cells in 2010 due to the closure of a large manufacturing plant (e.g., Owens-Illinois Glass manufacturers in 2006). The red cell to the west of the city highlights one of the newly developed job-rich areas. This reflects the expansion of Medco Health Solutions (development of Specialty Pharmacy Center of Excellence in 2003). As job-rich cells leave the center area, new centers emerge in remote locations leading to a higher degree of spatial dispersion.

<<<Figure 9 about here>>>

Conclusion

This study has proposed a new methodological approach to address the question of the degree of employment decentralization across metropolitan areas in the U.S. Whereas studies on this question typically adopt an approach that first attempts to measure job subcenters, we have proposed an alternative approach that sidesteps the methodological challenges of attempting to define and measure employment subcenters which have been increasingly reported in the literature (Gardner and Marlay 2013; Hajrasouliha and Hamidi 2017). Our approach attempts to quantify the interregional and intertemporal variation of metropolitan spatial structure by measuring the degrees of employment deconcentration and spatial dispersion. This approach avoids the problem of comparing across MSAs of widely varying sizes, and the difficulty of defining subcenters. The two measures also each have a clear interpretation, and avoid the problem of attempting to distinguish between a monocentric, polycentric, or scattered pattern of employment in an area.

Our application of the new approach showed considerable variability in the degree of employment deconcentration in 2010 across MSAs. Whereas all MSAs exhibited a degree of employment concentration as 50% of jobs are concentrated in just 4.8% of the grid cells on average across MSAs, this deconcentration nonetheless differed notably across MSAs. We also found that there was variability across MSAs in how this deconcentration changed over the decade from 2000-10. Whereas most MSAs saw a modest increase in employment deconcentration across the decade, there were nonetheless a minority of MSAs that experienced more job concentration. Why this change varied across MSAs would be a natural usage of our measure and a potential future research area. And while data limited us to studying just this particular decade, exploring this same question using our measures on other time periods is also a natural direction for future work. Again, our measure of employment deconcentration has a clear interpretation, and does not encounter the difficulty of defining subcenters or various prickly issues such as measuring changes in the size of subcenters, or their locations.

Our measure of spatial dispersion also allowed for a clear interpretation. The average value of 56.4% across MSAs in 2010 indicated that the grid cells containing the top 50 percent of jobs are only 56% as spatially dispersed as are grid cells in these MSAs, on average. This clear interpretation allows not only comparing MSAs at a point in time, but also allows for historical comparisons within and across MSAs. We believe that such historical comparisons offer the opportunity for deeper understanding of the spatial dispersion of employment in metropolitan areas over time, and should open a rich avenue for empirical exploration. We also highlight that although our interest was not in explicitly addressing questions of monocentric versus polycentric versus scattered patterns, a metropolitan area's values on each of our two measures can provide insight in this regard. As we demonstrated, a MSA with low values on both deconcentration and spatial dispersion is most consistent with a monocentric pattern, whereas the combination of low deconcentration with high spatial dispersion is consistent with a polycentric pattern. Combining these measures in this way will make it easy for future researchers to detect MSAs to target for case study research on these patterns, and how they change over time.

A feature of our approach that we argued is also a theoretical advantage is that we can define different proportions of grid cells in an MSA for measuring the level of deconcentration. Rather than considering the "proper" percentage of employment to measure (e.g., 50%, 60%, 70%, etc.), we believe that the level of concentration at these different extents is of substantive interest. It is therefore useful to make a distinction regarding how much employment deconcentration exists at these different extents. We point out that this is somewhat analogous to the approach of Reardon and colleagues (Reardon, Matthews, O'Sullivan, Lee, Firebaugh, Farrell, and Bischoff 2008) who measured racial segregation at different spatial scales and emphasized that there can be different theoretical explanations for the degree of segregation at different scales. We argue that a similar possibility exists for the degree of employment deconcentration at different extents. This opens the possibility for future research to ask what features of MSAs might explain deconcentration at different scales.

A desirable feature of our measures is that it is straightforward to use them to compute measures of change over time. Whereas measuring change over time based on employment subcenters is difficult given the possible change in the size of subcenters themselves, or how they move (Kane, Hipp, and Kim 2018), our continuous measures are readily used to measure change by simply computing the difference in values over time. We demonstrated that these measures of change can illustrate how MSAs evolve on each of these dimensions. We also demonstrated that our approach yields additional insights, as an MSA may increase on spatial dispersion but not on employment deconcentration, or vice versa. Thus, incorporating both of our measures provides key insights to researchers wishing to study the evolution of the spatial structure of employment across metropolitan areas over time. Focusing on change over time raises the question of how to account for boundary changes in MSAs over time; we chose to use fixed boundaries as we believe this provides the most direct comparison over time. Nonetheless, it is straightforward to use our approach with different boundaries at the two time points if the researcher prefers that approach.

We acknowledge some limitations of this study. Although we proposed using a strategy that does not attempt to measure employment subcenters, there is nonetheless the challenge of defining the smaller geographic units to measure employment. We used one square kilometer grid cells across the entire U.S., although there is no reason for this to be the single appropriate cell size. Future research will need to explore how much of an effect this decision has on the results—we suspect that results will not be very sensitive to a change in cell size given that our strategy is simply ordering the grid cells by employment levels rather than attempting to create subcenters, in which the cell size can impact the results more substantially (Kane, Hipp, and Kim 2018). But this should be assessed in future research. Second, we created separate measures capturing employment deconcentration and spatial dispersion, rather than a single measure of them. Although some may view this as a limitation, our view is that there is a conceptual distinction between the level of employment deconcentration in general and how spatially concentrated it is, and therefore it is useful to treat these as two separate dimensions. We demonstrated how each of these measures provides unique insights. Third, defining the macro area is also challenging. The boundaries of metropolitan areas are sometimes unclear, and Census definitions based on County boundaries can include large open areas. This latter issue can bias estimates of concentration, and we therefore used urbanized areas, but this general challenge should be kept in mind.

Despite these limitations, the present approach appears to have merit. With minimal methodological arbitrariness, it enables researchers to measure key characteristics of metropolitan spatial structure and their variability across regions and over time. We believe our approach will be useful for future scholars exploring how these patterns evolve over longer periods of time and what they entail.

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Tables and Figures

Table 1. Means and standard deviations of deconcentration and spatial dispersion measures for all MSA's in 2000, 2010, and change from 2000 to 2010

	50%	60%	70%	80%
2000 deconcentration				
Average	4.0%	6.2%	9.4%	14.2%
Standard deviation	1.5%	2.0%	2.6%	3.4%
2010 deconcentration				
Average	4.8%	7.4%	11.1%	16.5%
Standard deviation	1.6%	2.1%	2.7%	3.5%
Deconcentration change from 2000 to 2010				
Average	0.8%	1.2%	1.7%	2.3%
Standard deviation	0.8%	0.9%	1.2%	1.4%
2000 spatial dispersion				
Average	54.7%	57.8%	61.2%	64.0%
Standard deviation	19.6%	17.5%	16.0%	15.2%
2010 spatial dispersion				
Average	56.4%	59.9%	62.6%	66.0%
Standard deviation	18.1%	16.8%	15.6%	14.4%
Spatial dispersion change from 2000 to 2010				
Average	1.8%	2.1%	1.4%	2.0%
Standard deviation	11.6%	9.2%	6.9%	5.5%
N=329 MSAs				

Table 2. Measures of employment deconcentration and spatial dispersion in 2000 and 2010 for 40 largest metropolitan areas, based on top 50% of employees

		2000				2010				2000-2010				
	MSA	Deconcentration	Z score	Spatial dispersion	Z score	Deconcentration	Z score	Spatial dispersion	Z score	Change in Deconcentration	Z score	Change in Spatial dispersion	Z score	Population
1	New York, NY PMSA	1.6%	-1.60	17.8%	-1.88	1.5%	-2.11	17.3%	-2.15	-0.1%	-1.22	-0.4%	-0.19	9,358,032
2	Los Angeles-Long Beach, CA PMSA	8.2%	2.81	62.1%	0.38	8.5%	2.29	65.9%	0.52	0.2%	-0.78	3.8%	0.18	8,968,758
3	Chicago, IL PMSA	5.8%	1.17	56.9%	0.11	6.4%	0.96	61.4%	0.27	0.6%	-0.30	4.5%	0.24	7,476,984
4	Houston, TX PMSA	3.9%	-0.06	46.9%	-0.39	5.3%	0.27	54.6%	-0.10	1.4%	0.69	7.7%	0.52	5,300,962
5	Philadelphia, PA-NJ PMSA	5.1%	0.70	58.9%	0.22	5.8%	0.63	62.5%	0.33	0.8%	-0.07	3.6%	0.16	5,116,979
6	Washington, DC-MD-VA-WV PMSA	2.8%	-0.79	42.9%	-0.60	3.1%	-1.05	50.4%	-0.33	0.3%	-0.62	7.4%	0.49	4,939,030
7	Atlanta, GA MSA	3.4%	-0.41	52.5%	-0.11	4.3%	-0.35	57.8%	0.08	0.9%	0.08	5.4%	0.31	4,766,290
8	Detroit, MI PMSA	6.9%	1.93	56.9%	0.12	7.5%	1.66	61.2%	0.27	0.5%	-0.35	4.3%	0.22	4,273,939
9	Riverside-San Bernardino, CA PMSA	3.7%	-0.17	61.3%	0.34	4.4%	-0.25	64.6%	0.45	0.7%	-0.19	3.3%	0.13	3,993,041
10	Dallas, TX PMSA	3.9%	-0.08	44.9%	-0.50	4.5%	-0.19	44.0%	-0.68	0.6%	-0.23	-0.8%	-0.22	3,845,033
11	Phoenix-Mesa, AZ MSA	5.2%	0.81	50.7%	-0.20	6.8%	1.27	52.0%	-0.24	1.6%	1.03	1.3%	-0.04	3,452,748
12	Boston, MA-NH PMSA	3.5%	-0.30	41.5%	-0.67	3.0%	-1.13	38.8%	-0.97	-0.5%	-1.74	-2.7%	-0.39	3,358,669
13	Minneapolis-St. Paul, MN-WI MSA	3.7%	-0.19	44.3%	-0.53	4.7%	-0.06	48.2%	-0.45	1.0%	0.25	4.0%	0.19	2,964,892
14	San Diego, CA MSA	3.9%	-0.04	49.6%	-0.26	4.6%	-0.12	57.2%	0.04	0.7%	-0.17	7.6%	0.51	2,877,755
15	Orange County, CA PMSA	9.0%	3.33	64.2%	0.49	10.0%	3.25	68.3%	0.65	1.0%	0.20	4.0%	0.20	2,703,398
16	Nassau-Suffolk, NY PMSA	7.8%	2.49	63.2%	0.44	7.3%	1.58	64.2%	0.43	-0.4%	-1.60	0.9%	-0.07	2,650,268
17	St. Louis, MO-IL MSA	4.1%	0.05	50.6%	-0.21	5.5%	0.40	55.3%	-0.06	1.4%	0.73	4.7%	0.25	2,566,869
18	Baltimore, MD PMSA	4.2%	0.14	57.6%	0.15	4.7%	-0.06	60.1%	0.21	0.5%	-0.41	2.6%	0.07	2,561,764
19	Tampa-St. Petersburg-Clearwater, FL MSA	5.9%	1.26	64.4%	0.50	6.8%	1.23	65.2%	0.48	0.9%	0.07	0.8%	-0.09	2,438,187
20	Oakland, CA PMSA	6.5%	1.63	84.9%	1.54	6.4%	0.99	80.3%	1.31	-0.1%	-1.14	-4.6%	-0.55	2,334,981
21	Seattle-Bellevue-Everett, WA PMSA	2.4%	-1.09	42.3%	-0.63	3.2%	-1.03	50.7%	-0.31	0.8%	0.00	8.4%	0.58	2,329,942
22	Miami, FL PMSA	8.7%	3.14	59.9%	0.27	9.0%	2.62	66.6%	0.56	0.3%	-0.72	6.7%	0.42	2,306,991
23	Cleveland-Lorain-Elyria, OH PMSA	5.1%	0.70	57.4%	0.14	5.9%	0.65	61.9%	0.30	0.8%	-0.03	4.6%	0.24	2,167,445
24	Denver, CO PMSA	6.3%	1.50	52.9%	-0.09	7.1%	1.40	59.8%	0.19	0.8%	-0.04	7.0%	0.45	2,143,758
25	Pittsburgh, PA MSA	3.1%	-0.62	64.9%	0.52	4.2%	-0.41	64.1%	0.42	1.1%	0.35	-0.8%	-0.22	2,130,986
26	Newark, NJ PMSA	6.0%	1.34	64.6%	0.51	6.6%	1.13	58.0%	0.09	0.6%	-0.28	-6.6%	-0.72	2,030,196
27	Las Vegas, NV-AZ MSA	3.3%	-0.43	23.9%	-1.57	5.2%	0.25	24.9%	-1.73	1.9%	1.37	1.0%	-0.06	2,010,143
28	Portland-Vancouver, OR-WA PMSA	4.1%	0.08	45.3%	-0.48	5.3%	0.31	52.4%	-0.22	1.2%	0.49	7.2%	0.47	1,992,627
29	San Antonio, TX MSA	5.5%	1.01	53.7%	-0.05	6.1%	0.82	55.5%	-0.05	0.6%	-0.28	1.8%	0.00	1,929,521
30	Orlando, FL MSA	5.3%	0.84	56.8%	0.11	6.0%	0.73	62.9%	0.36	0.7%	-0.13	6.0%	0.37	1,924,777

31	Indianapolis, IN MSA	3.8%	-0.15	59.0%	0.22	3.5%	-0.84	54.2%	-0.12	-0.3%	-1.43	-4.8%	-0.57	1,824,672
32	Charlotte-Gastonia-Rock Hill, NC-SC MSA	2.5%	-1.00	65.2%	0.54	3.9%	-0.58	69.7%	0.73	1.4%	0.76	4.4%	0.23	1,806,375
33	San Francisco, CA PMSA	3.3%	-0.49	40.7%	-0.71	3.0%	-1.11	35.7%	-1.14	-0.2%	-1.33	-5.0%	-0.58	1,755,784
34	Sacramento, CA PMSA	4.6%	0.39	58.5%	0.20	6.2%	0.85	51.2%	-0.29	1.6%	0.99	-7.3%	-0.78	1,737,392
35	Kansas City, MO-KS MSA	4.1%	0.09	51.6%	-0.15	4.8%	0.00	55.6%	-0.04	0.7%	-0.18	4.0%	0.19	1,674,636
36	Cincinnati, OH-KY-IN PMSA	4.7%	0.48	50.2%	-0.23	5.0%	0.08	52.9%	-0.19	0.2%	-0.77	2.7%	0.08	1,669,623
37	Fort Worth-Arlington, TX PMSA	4.9%	0.62	60.1%	0.28	6.3%	0.94	68.7%	0.68	1.4%	0.74	8.6%	0.59	1,665,088
38	Norfolk-Virginia Beach-Newport News, VA-	5.0%	0.67	67.2%	0.64	5.8%	0.59	74.8%	1.01	0.7%	-0.10	7.6%	0.50	1,618,334
39	Columbus, OH MSA	4.8%	0.51	57.4%	0.14	5.2%	0.23	66.1%	0.53	0.4%	-0.53	8.7%	0.60	1,603,263
40	Fort Lauderdale, FL PMSA	10.5%	4.28	77.1%	1.14	11.5%	4.19	83.6%	1.50	1.0%	0.29	6.5%	0.41	1,527,925

Figure 1. Conceptual distinction between employment deconcentration and spatial dispersion measures

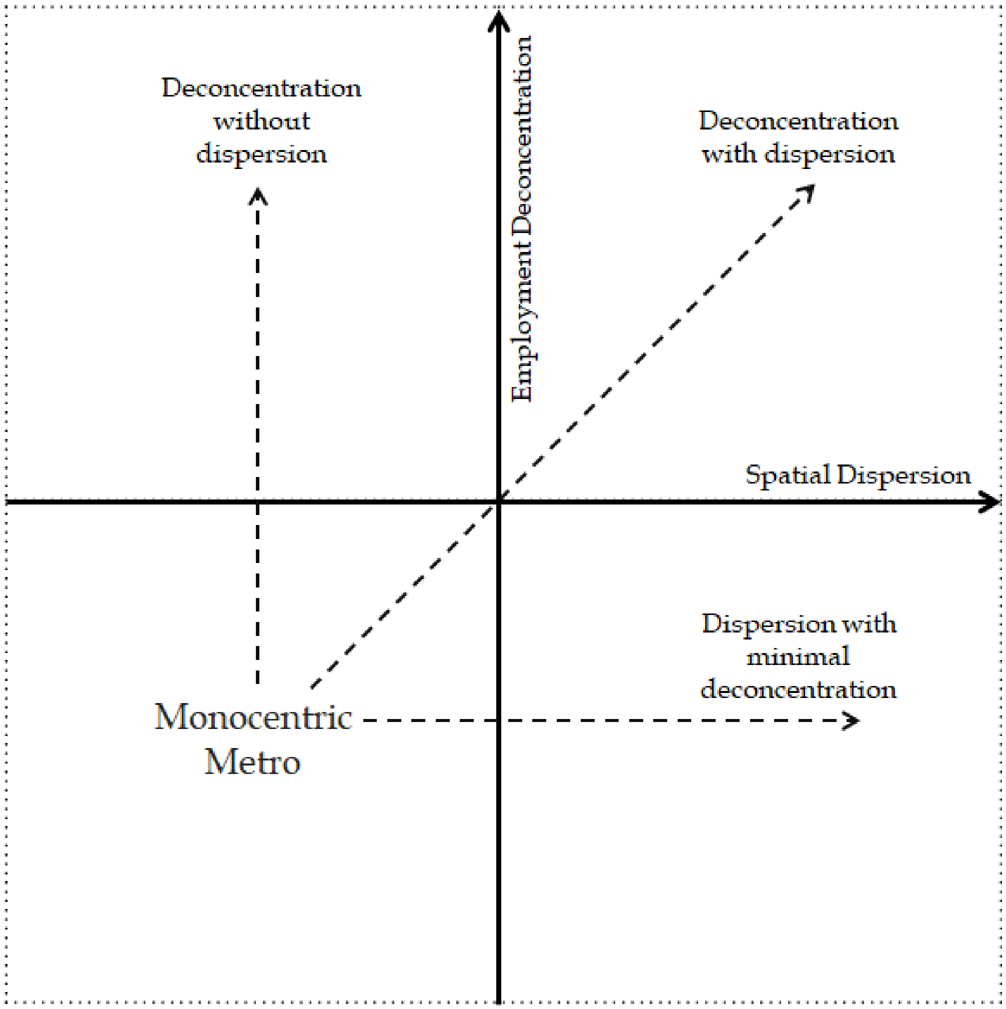


Figure 2. Stylized examples of employment concentration in regions

city1 Deconcentration = 2%, Dispersion = 9.7%

	1	2	3	4	5	6	7	8	9	10
1										
2										
3										
4										
5					98	98				
6										
7										
8										
9										
10										

city5 Deconcentration = 5%, Dispersion = 65.3%

	1	2	3	4	5	6	7	8	9	10
1										
2		25								
3				35						
4										
5					70					
6							35			
7										
8									25	
9										
10										

city2 Deconcentration = 5%, Dispersion = 28.7%

	1	2	3	4	5	6	7	8	9	10
1										
2										
3										
4										
5			25	35	70	35	25			
6										
7										
8										
9										
10										

city6 Deconcentration = 5%, Dispersion = 69.6%

	1	2	3	4	5	6	7	8	9	10
1										
2		35								
3				40						
4										
5					40					
6							40			
7										
8									35	
9										
10										

city3 Deconcentration = 5%, Dispersion = 57.1%

	1	2	3	4	5	6	7	8	9	10
1										
2		25								
3										
4										
5				35	70	35				
6										
7										
8									25	
9										
10										

city7 Deconcentration = 10%, Dispersion = 69.8%

	1	2	3	4	5	6	7	8	9	10
1										
2	15	15								
3				20	20					
4										
5				20	20					
6						20	20			
7										
8								15	15	
9										
10										

city4 Deconcentration = 5%, Dispersion = 61.5%

	1	2	3	4	5	6	7	8	9	10
1										
2		35								
3										
4										
5				25	70	25				
6										
7										
8									35	
9										
10										

city8 Deconcentration = 10%, Dispersion = 79.2%

	1	2	3	4	5	6	7	8	9	10
1				15						
2		15						20		
3						20				
4			20							
5					20					
6							20			
7				20						
8									15	
9				15						
10										

Note: 10x10 cells for each hypothetical region. Numbers are employees in cells. All empty cells have 2 employees each (not shown for clarity)

Figure 3

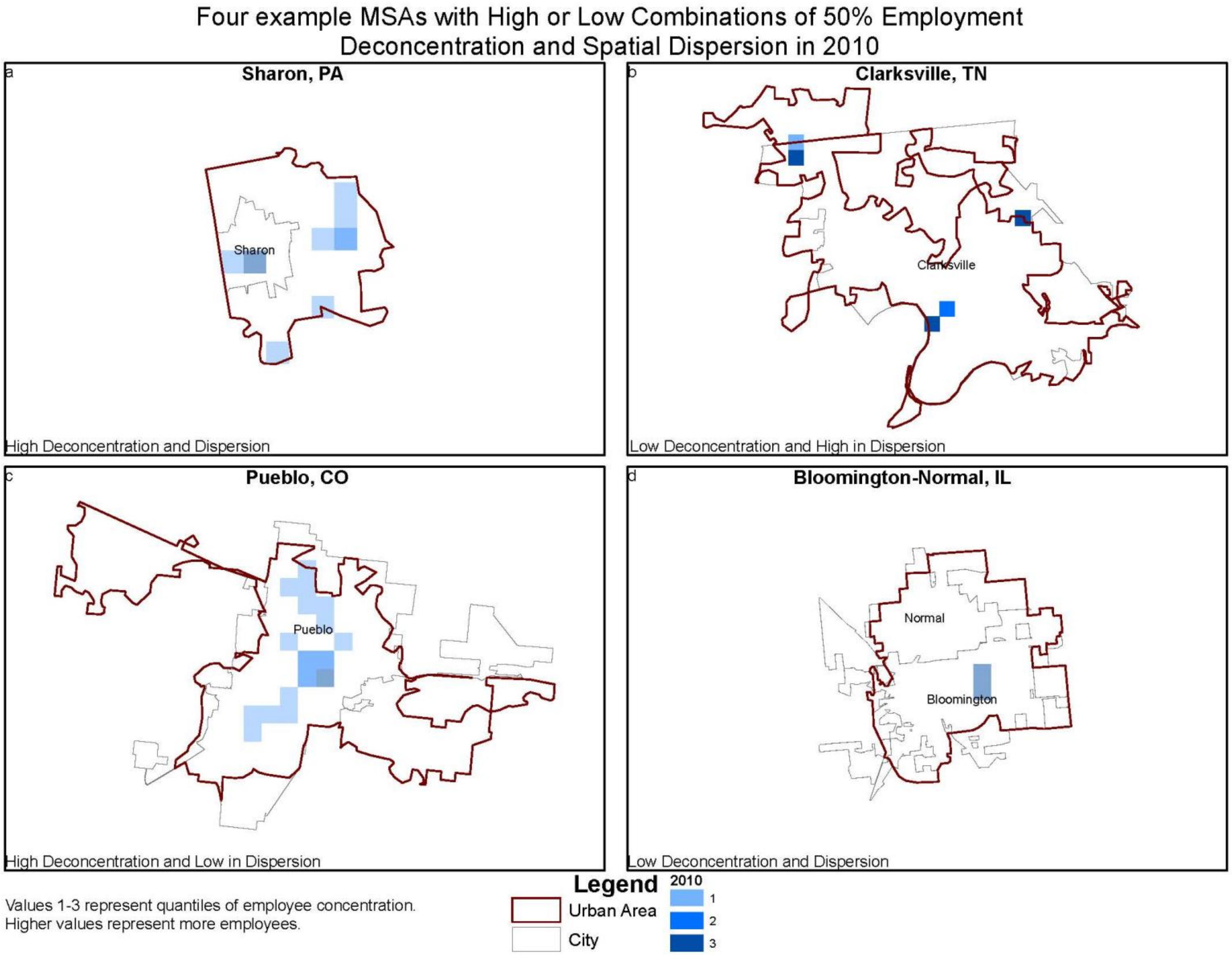
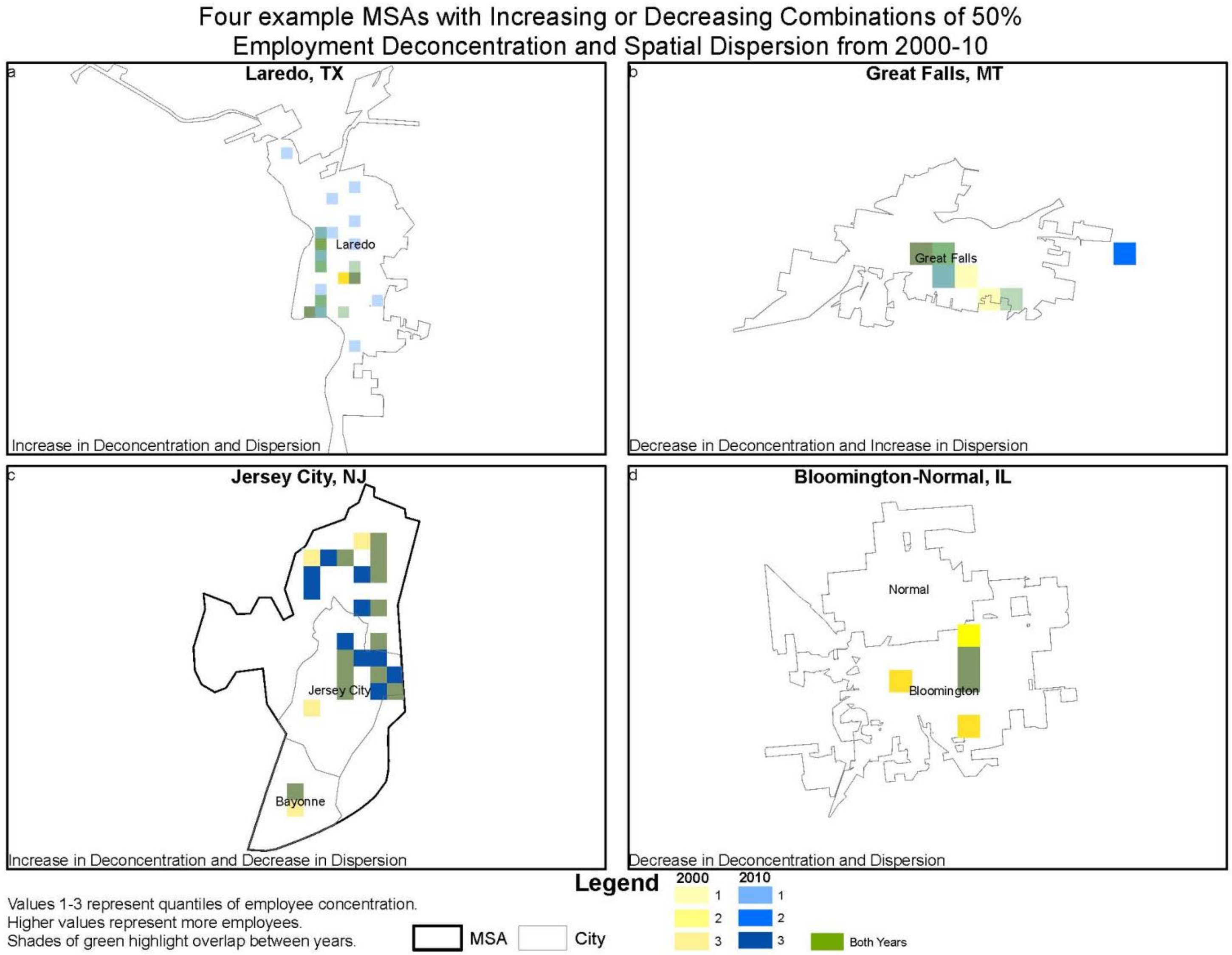

Four example MSAs with High or Low Combinations of 50% Employment Deconcentration and Spatial Dispersion in 2010
a
Sharon, PA
Sharon
High Deconcentration and Dispersion
b
Clarksville, TN
Clarksville
Low Deconcentration and High in Dispersion
c
Pueblo, CO
Pueblo
High Deconcentration and Low in Dispersion
d
Bloomington-Normal, IL
Normal
Bloomington
Low Deconcentration and Dispersion
Values 1-3 represent quantiles of employee concentration.
Higher values represent more employees.
Legend
Urban Area
City
2010
1
2
3

Figure 4


Four example MSAs with Increasing or Decreasing Combinations of 50%
Employment Deconcentration and Spatial Dispersion from 2000-10
a
Laredo, TX
Laredo
Increase in Deconcentration and Dispersion
b
Great Falls, MT
Great Falls
Decrease in Deconcentration and Increase in Dispersion
c
Jersey City, NJ
Jersey City
Bayonne
Increase in Deconcentration and Decrease in Dispersion
d
Bloomington-Normal, IL
Normal
Bloomington
Decrease in Deconcentration and Dispersion
Legend
2000
2010
1
2
3
1
2
3
Both Years
Values 1-3 represent quantiles of employee concentration.
Higher values represent more employees.
Shades of green highlight overlap between years.
MSA
City

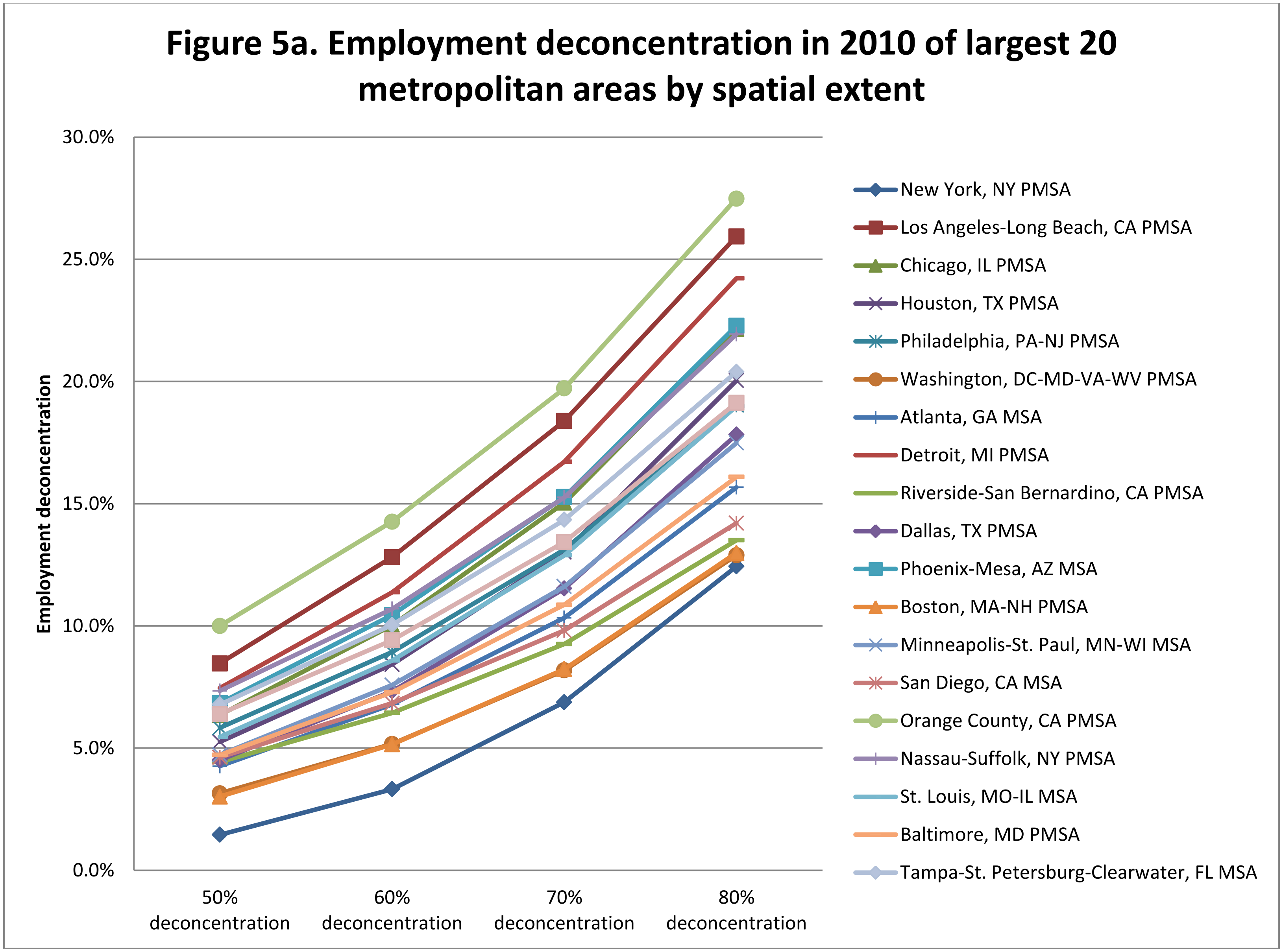


Figure 5a. Employment deconcentration in 2010 of largest 20 metropolitan areas by spatial extent
Employment deconcentration
30.0%
25.0%
20.0%
15.0%
10.0%
5.0%
0.0%
50% deconcentration
60% deconcentration
70% deconcentration
80% deconcentration
New York, NY PMSA
Los Angeles-Long Beach, CA PMSA
Chicago, IL PMSA
Houston, TX PMSA
Philadelphia, PA-NJ PMSA
Washington, DC-MD-VA-WV PMSA
Atlanta, GA MSA
Detroit, MI PMSA
Riverside-San Bernardino, CA PMSA
Dallas, TX PMSA
Phoenix-Mesa, AZ MSA
Boston, MA-NH PMSA
Minneapolis-St. Paul, MN-WI MSA
San Diego, CA MSA
Orange County, CA PMSA
Nassau-Suffolk, NY PMSA
St. Louis, MO-IL MSA
Baltimore, MD PMSA
Tampa-St. Petersburg-Clearwater, FL MSA

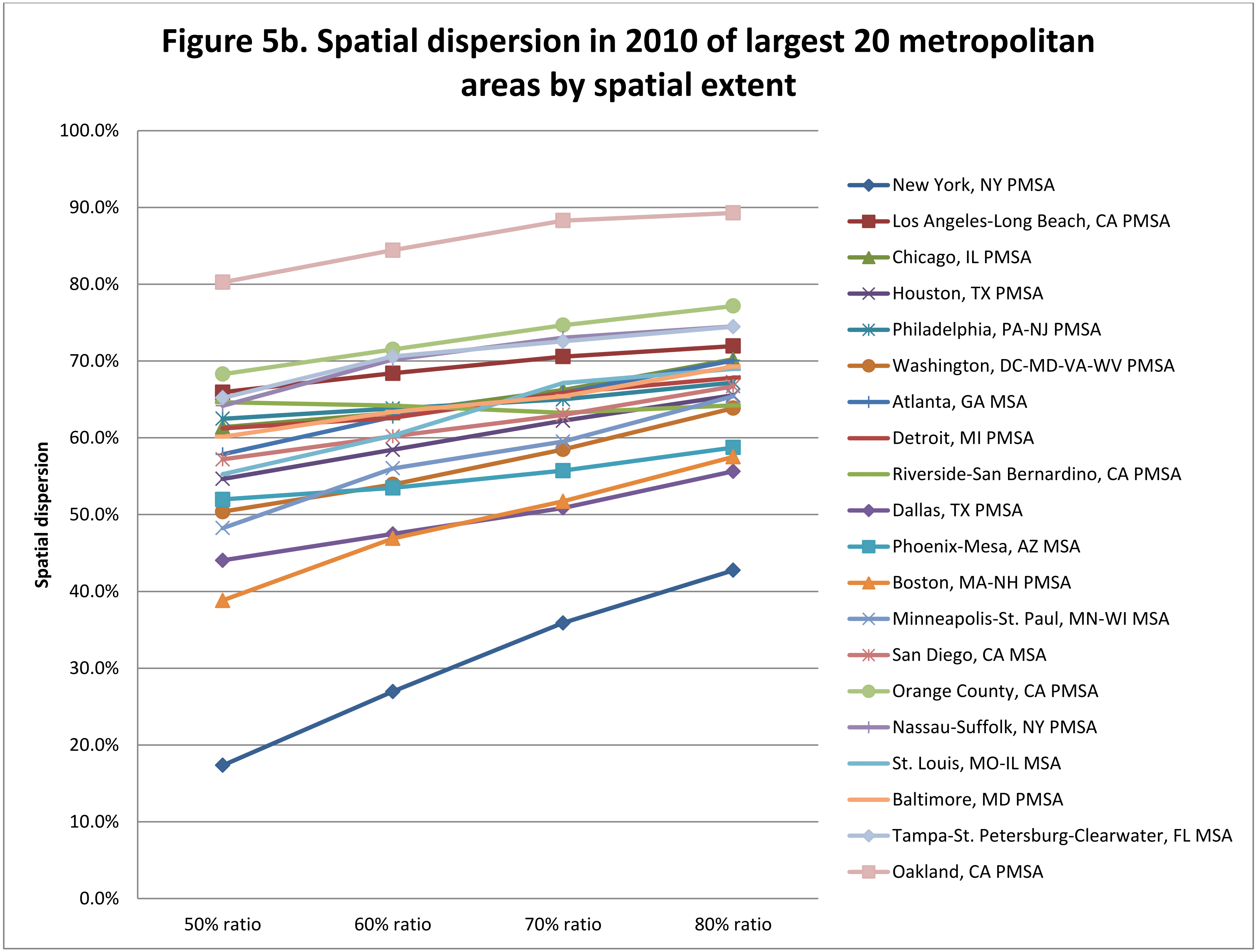


Figure 5b. Spatial dispersion in 2010 of largest 20 metropolitan areas by spatial extent
Spatial dispersion
100.0%
90.0%
80.0%
70.0%
60.0%
50.0%
40.0%
30.0%
20.0%
10.0%
0.0%
50% ratio
60% ratio
70% ratio
80% ratio
New York, NY PMSA
Los Angeles-Long Beach, CA PMSA
Chicago, IL PMSA
Houston, TX PMSA
Philadelphia, PA-NJ PMSA
Washington, DC-MD-VA-WV PMSA
Atlanta, GA MSA
Detroit, MI PMSA
Riverside-San Bernardino, CA PMSA
Dallas, TX PMSA
Phoenix-Mesa, AZ MSA
Boston, MA-NH PMSA
Minneapolis-St. Paul, MN-WI MSA
San Diego, CA MSA
Orange County, CA PMSA
Nassau-Suffolk, NY PMSA
St. Louis, MO-IL MSA
Baltimore, MD PMSA
Tampa-St. Petersburg-Clearwater, FL MSA
Oakland, CA PMSA

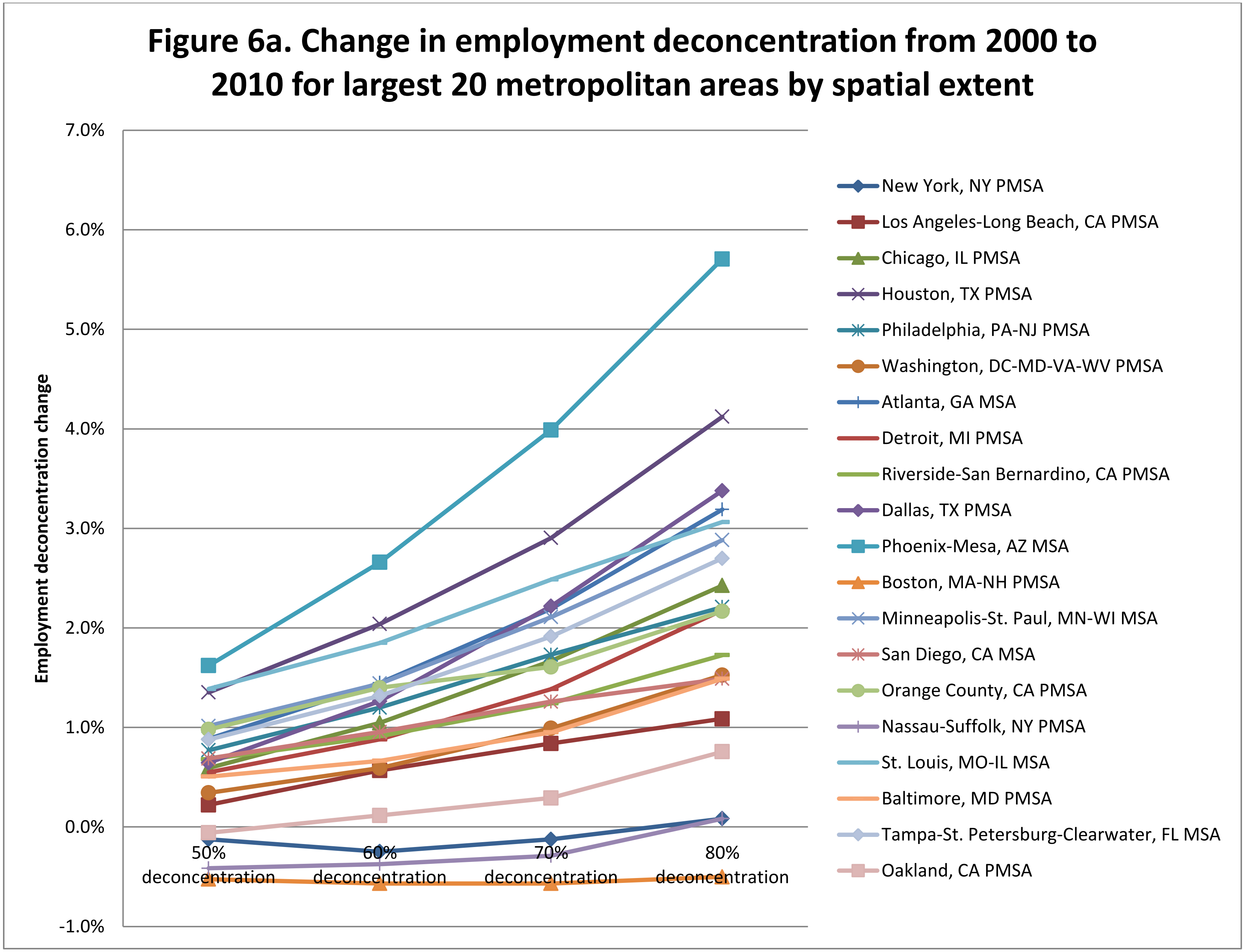


Figure 6a. Change in employment deconcentration from 2000 to 2010 for largest 20 metropolitan areas by spatial extent
Employment deconcentration change
7.0%
6.0%
5.0%
4.0%
3.0%
2.0%
1.0%
0.0%
-1.0%
50% deconcentration
60% deconcentration
70% deconcentration
80% deconcentration
New York, NY PMSA
Los Angeles-Long Beach, CA PMSA
Chicago, IL PMSA
Houston, TX PMSA
Philadelphia, PA-NJ PMSA
Washington, DC-MD-VA-WV PMSA
Atlanta, GA MSA
Detroit, MI PMSA
Riverside-San Bernardino, CA PMSA
Dallas, TX PMSA
Phoenix-Mesa, AZ MSA
Boston, MA-NH PMSA
Minneapolis-St. Paul, MN-WI MSA
San Diego, CA MSA
Orange County, CA PMSA
Nassau-Suffolk, NY PMSA
St. Louis, MO-IL MSA
Baltimore, MD PMSA
Tampa-St. Petersburg-Clearwater, FL MSA
Oakland, CA PMSA

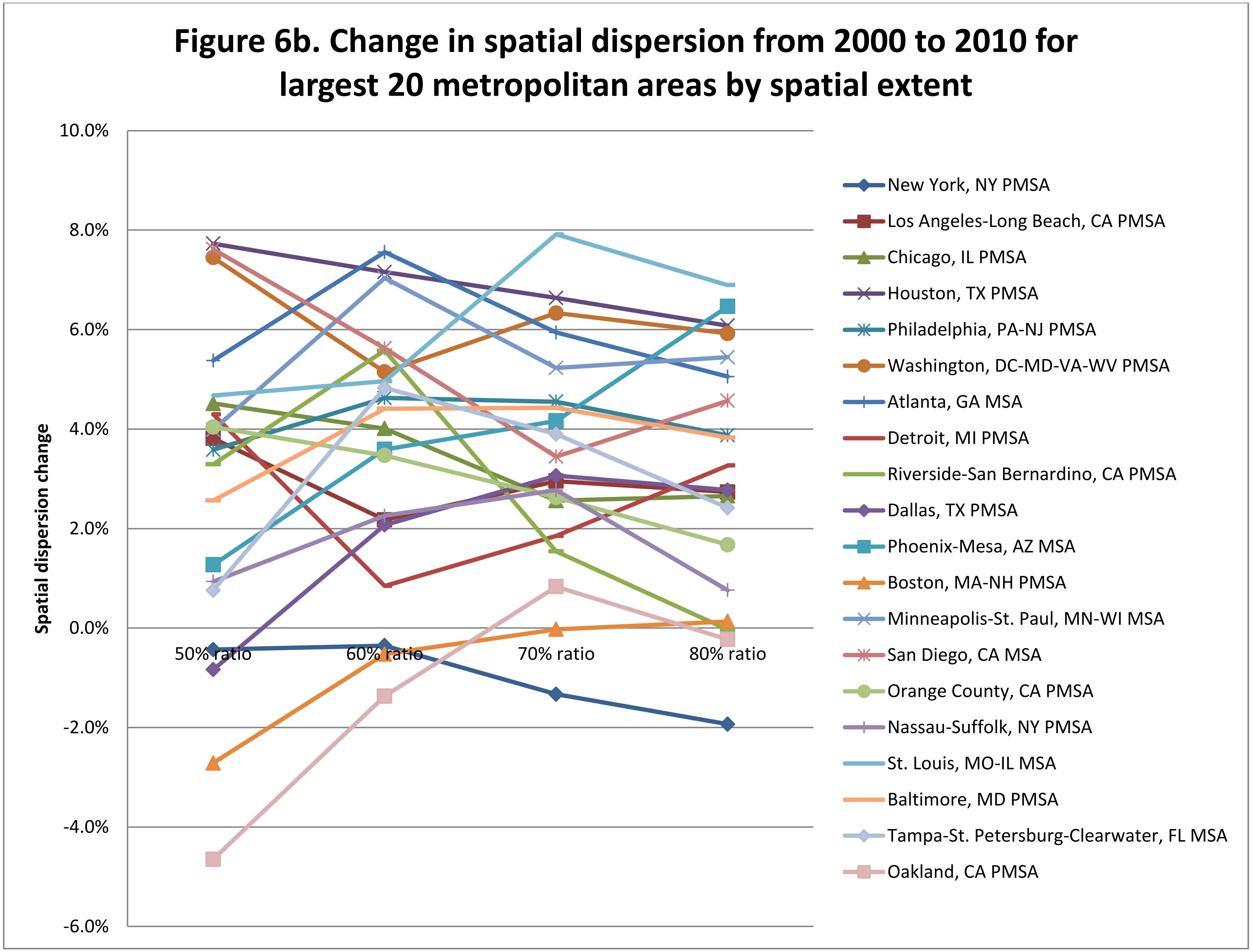


Figure 6b. Change in spatial dispersion from 2000 to 2010 for largest 20 metropolitan areas by spatial extent
Spatial dispersion change
10.0%
8.0%
6.0%
4.0%
2.0%
0.0%
-2.0%
-4.0%
-6.0%
50% ratio
60% ratio
70% ratio
80% ratio
New York, NY PMSA
Los Angeles-Long Beach, CA PMSA
Chicago, IL PMSA
Houston, TX PMSA
Philadelphia, PA-NJ PMSA
Washington, DC-MD-VA-WV PMSA
Atlanta, GA MSA
Detroit, MI PMSA
Riverside-San Bernardino, CA PMSA
Dallas, TX PMSA
Phoenix-Mesa, AZ MSA
Boston, MA-NH PMSA
Minneapolis-St. Paul, MN-WI MSA
San Diego, CA MSA
Orange County, CA PMSA
Nassau-Suffolk, NY PMSA
St. Louis, MO-IL MSA
Baltimore, MD PMSA
Tampa-St. Petersburg-Clearwater, FL MSA
Oakland, CA PMSA

Figure 7. Simultaneous change in employment deconcentration and spatial dispersion based on top 50% of jobs for 20 largest MSAs

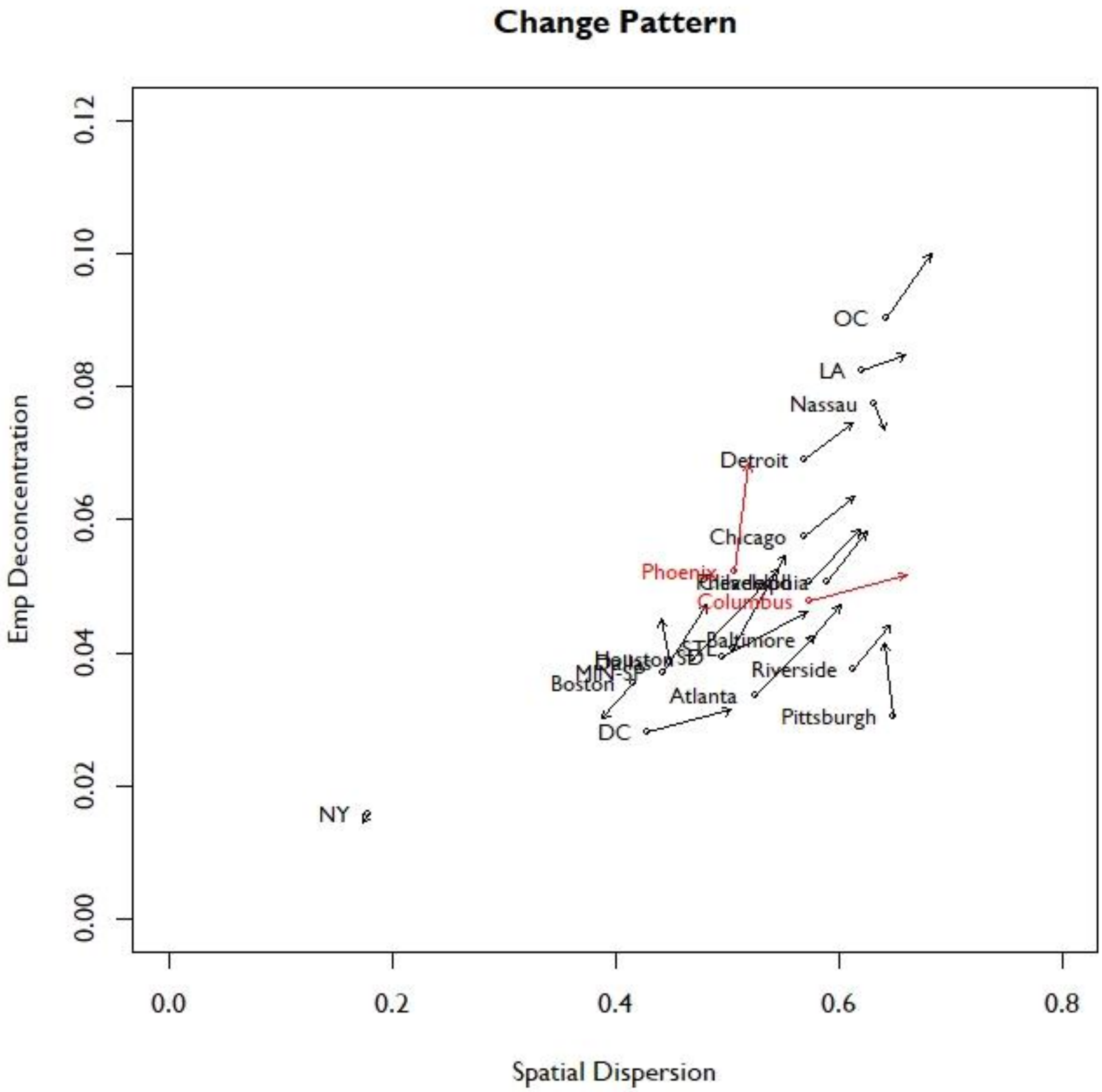
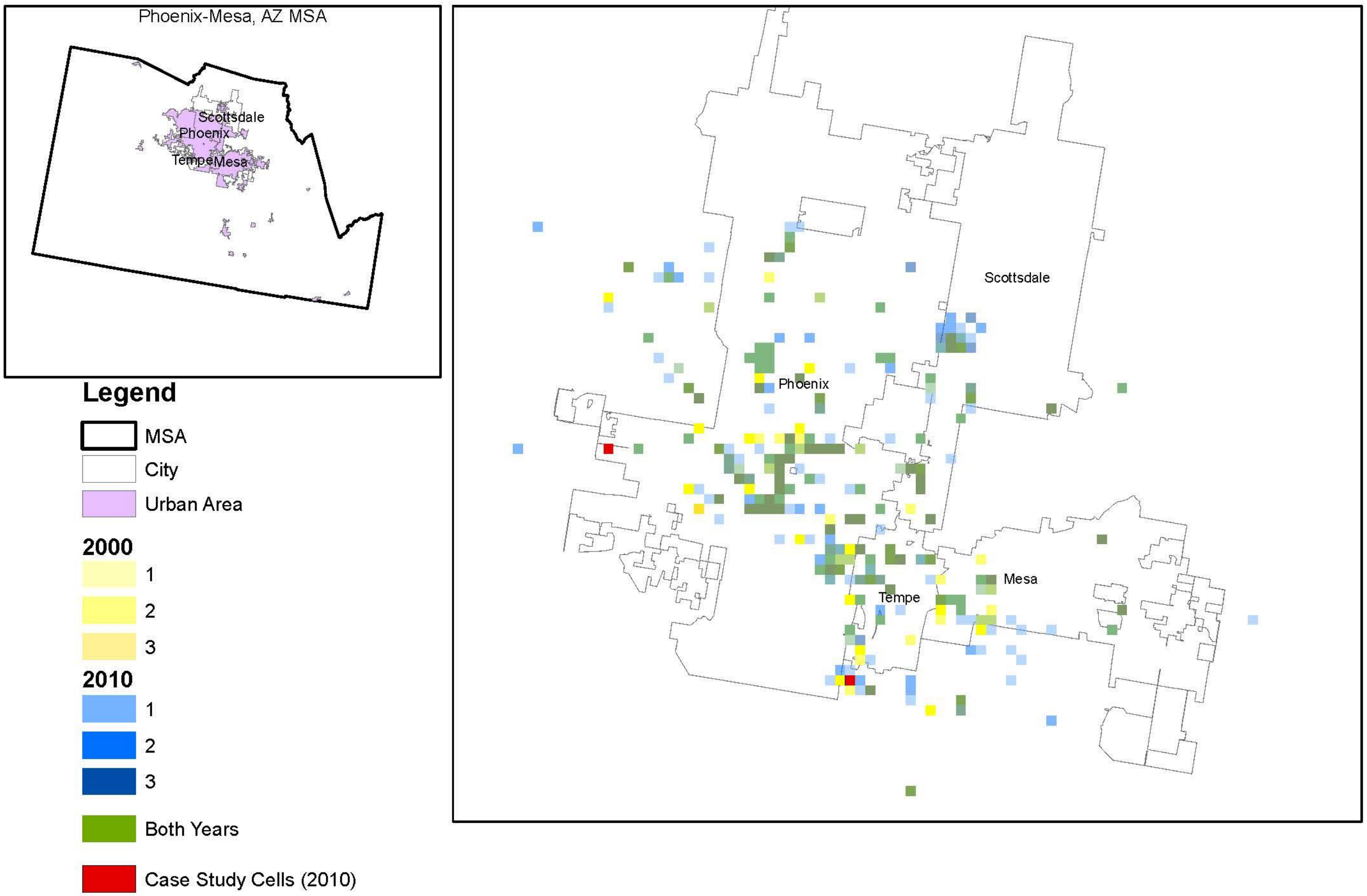


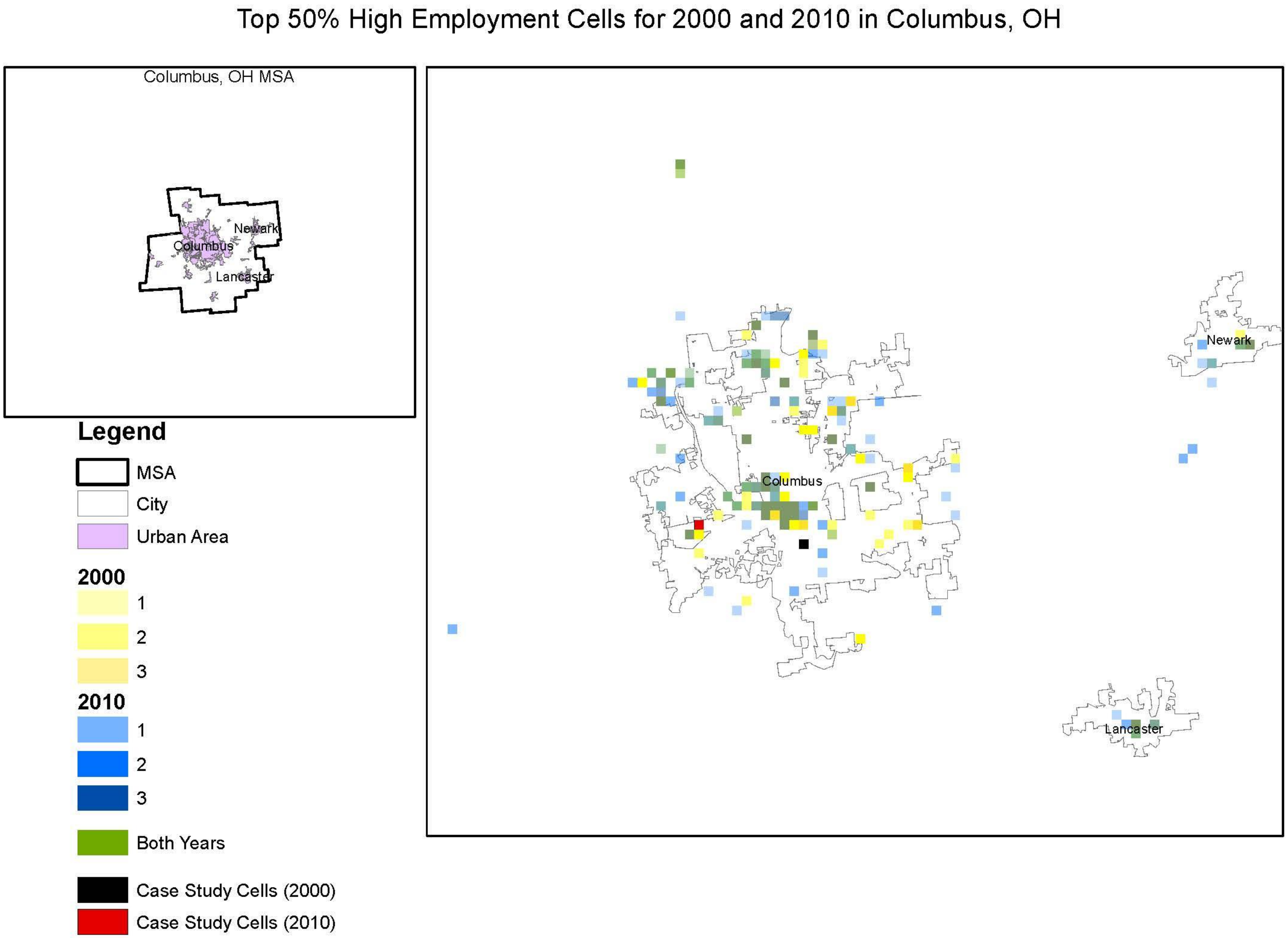
Figure 8.

Top 50% High Employment Cells for 2000 and 2010 in Phoenix-Mesa, AZ



Values 1-3 represent quantiles of employee concentration.
Higher values represent more employees.
Shades of green highlight overlap between years.

Figure 9.



Values 1-3 represent quantiles of employee concentration.
Higher values represent more employees.
Shades of green highlight overlap between years.