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The typology of the American metropolis: monocentricity, polycentricity, or generalized dispersion?

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ABSTRACT
Although the spatial structure of employment in large US metropolitan regions is a well-researched topic, few studies focus on medium-sized and small US metropolitan regions. Consequently, there is no overall typology relating small-to-medium urban form to employment distribution. We address this gap by investigating the spatial structure of employment in 356 metropolitan regions. We conceptualize six typologies based on three categories that have overlapping properties: "monocentricity," "polycentricity," and "generalized dispersion." The study has three main findings. First, the three types of urban form that we identify as "hybrid" outnumber the three "pure" types by almost four to one. Second, job dispersion is a dominant characteristic in almost 70% of all metropolitan statistical areas (MSAs) (including the hybrid types), and polycentricity (56.7% of MSAs) is somewhat more common than monocentricity. Third, there is a strong relationship between population size and density. The population of medium-sized metropolitan areas is generally more dispersed than that of small and large metropolitan areas. Polycentricy emerges mostly in large metropolitan regions, while monocentrity is found in both small and large metropolitan regions.

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1. Introduction

Arguments for and against the compact city are numerous. Proponents of urban density believe that compact development has economic, social, and environmental advantages, such as affordable public transportation, reduction of traffic congestion, lower energy consumption, open space preservation, efficient infrastructure, increasing opportunities for social interactions, improving public health, and increased vitality of the public realm (Anderson, Kanaroglou, & Miller, 1996; Ewing, 1997; Ewing & Cervero, 2010; Florida, 2014; Graham & Marvin, 1996; Jacobs, 1961; Nelson, Dawkins, & Sanchez, 2007; Thomas & Cousins, 1996). On the other hand, opponents of density argue that compact development produces lower quality of life due to increased air pollution and traffic congestion, lower availability of affordable housing, minimal use of solar energy, and financial speculation on

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housing (e.g. Breheny, 1992; Gordon & Richardson, 1997; Green, 1996; Holcombe & Williams, 2010; Kahn, 2006; Knight, 1996).

Meanwhile, many authors advocate the concept of decentralized concentration, or a so-called polycentric urban form to explain the spatiality of densifying cities. This spatial pattern has the advantages of centralization in the form of spatial clusters while allowing the inevitable decentralization to towns and suburbs (Garreau, 1991; Yang, French, Holt, & Zhang, 2012). A region with no significant spatial clustering has a spatial pattern known as "generalized dispersion." This does not necessarily mean low overall density; it means minimal employment clustering in the region. For example, Gordon and Richardson (1996) examine the distribution of employment among subcenters in the Los Angeles metropolitan region in 1970, 1980, and 1990. The results show that the number of centers declined and the proportion of regional jobs located in subcenters is small and fell from year to year. The results suggest that the Los Angeles region may in the future become less "polycentric" and tend more towards "generalized dispersion."

Generalized dispersion is linked to similar terms including scatteration and dispersal (Shearmur, Coffey, Dube, & Barbonne, 2007) and edgeless city (Lang, 2003). As Lang (2003) argues in *Edgeless Cities: Exploring the Elusive Metropolis*, these areas are not mixed-use, pedestrian-friendly areas, nor are they easily accessed by public transit. In the United States, for example, two-thirds of office spaces are located outside downtowns, producing many edgeless cites in places, such as central New Jersey (Greater Princeton) (Lang, 2003). The key and challenging question, however, is whether generalized dispersion is the dominant spatial characteristic of American metropolis. To answer this question, we must begin by defining various types of metropolitan regions. For example, we must define how much concentration of employment and spatial clustering of housing is considered "compact" or at what number of centers "polycentricity" ceases and "generalized dispersion" begins (e.g. Gordon & Richardson, 1996; Ewing, 1997 or Garreau, 1991; Lang, 2003).

Although there is not a standard method for measuring and defining contemporary metropolitan form, there is a consensus among scholars that the US metropolitan statistical areas (MSAs) have in the past several decades experienced a spatial transformation due to decentralization of population and employment, decline of the central business district (CBD), and in many cases the emergence of employment centers outside the CBD. Studying these trends requires the development of spatial concepts for describing the evolving structure of metropolitan regions. Centralization—the degree of employment (or population) clustering at main center—and polycentricity —the degree of employment (or population) clustering at subcenters—are the two key spatial concepts widely used in this field (e.g.. Giuliano, Redfearn, Agarwal, Li, & Zhuang, 2007; Lee, 2007; Redfearn, 2007; Yang et al., 2012). However, a lack of consistency in operationalizing these two constructs is evident. In addition, the majority of studies on this subject focused on large metropolitan regions (e.g. Anderson & Bogart, 2001; Cutsinger & Galster, 2006; Giuliano et al., 2007; Lee, 2007; McMillen & McDonald, 1998; McMillen & Smith, 2003; Redfearn, 2007; Yang et al., 2012). There is clearly a gap in the literature for understanding the spatial structure of employment in small- and medium-sized metropolitan regions, and whether this structure follows the same trends seen in large metropolitan regions.

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In this study, we address this gap by developing polycentricity and centralization indices for all MSAs in the United States. We use 2010 census data and construct a national employment dataset, which covers 356 MSAs. We also propose a new typology for US metropolitan regions based on their polycentricity and centralization indices. The proposed typology provides a view of the current spatial structure of employment clustering in US metropolitan regions. This study provides a theoretical framework for future research on the relationship between regional employment structures and a wide range of social issues, including commuting, housing, inequality, and environmental justice.

This paper is divided into five sections. Section 1 provides a brief literature review on the spatial structure of metropolitan regions in the United States and methods of identifying employment centers and subcenters. In Section 2, we identify the centers and subcenters for all 356 US MSAs. Section 3 contains the operationalization of our polycentricity and centralization indices based on the defined centers. In Section 4, we propose a typology of the American metropolis based on the polycentricity and centralization indices. Finally, in the Section 5, we examine the relationship between our proposed typology and the population size and density of the metropolitan areas.

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2. Literature review

2.1. *Spatial structure of employment in the American metropolis*

Alonso's (1964) monocentric model was for many years the most influential depiction of urban structure. After its conception, the model was quickly extended to explain other spatial structures, such as production, transport, agricultural land, and housing (Anas, Arnott, & Small, 1998). However, many scholars have argued that the emerging urban spatial structure seen in US cities is actually polycentric (Anas et al., 1998; Garreau, 1991); others argue that it is best described as dispersed, or without significant employment centers (Lang, 2003). Those who argue for polycentricity claim that agglomeration economies can thrive outside central business districts (CBDs), benefiting from less traffic congestion, and lower land prices. Others believe that, due to rapid transit and advanced communication technology, the economic necessity of clustering has faded and generalized dispersion has become the more common—and more theoretically accurate—form of employment location (Gordon & Richardson, 1996).

Despite the general trend of decentralization, centers of employment can and do emerge (now largely outside of the CBDs) because of government incentives or private corporations cost–benefit analyses. In the former case, local governments use tax and land use policies (Zhang & Sasaki, 1997, 2000). Private developers and large firms can respond both to government incentives and the lower land rents and cheaper labor located outside of CBDs (Brasington, 2001; Fujita & Thisse, 2013).

The trend of declining employment is not limited to CBDs; in recent years, decline has also occurred in central cities and suburbs. Gordon et al.'s (1998) examination of employment trends between 1969 and 1994 across metropolitan and nonmetropolitan regions found that decentralization was persistent, often occurring beyond the suburbs into both exurban areas and rural areas. These authors found that:

> the location decisions of households are influenced less by workplace accessibility than the availability of amenities, recreational opportunities and public safety. In addition, the locations of firms are clearly becoming more footloose under the influence of the information revolution just at a time when core agglomeration diseconomies appear to be outweighing the original agglomeration economies that pulled people and economic activities together (Gordon et al., 1998, 1053).

Using the US census public use microdata sample data, Lee, Seo, and Webster (2006) found a similar employment trend from 1980 to 1990 for 12 US central metropolitan statistical areas (CMSAs) including Buffalo, New York, Philadelphia, Chicago, Cleveland, Detroit, Houston, Los Angeles, Denver, Portland, San Francisco, and Seattle. They divided each CMSA between two categories: the central city and all other areas. In all cases, the total central city share of employment declined over time. New York and Chicago had the lowest central city share loss, and Cleveland and Detroit had the highest decline of the central city.

Lee (2007) studied spatial trend in six US metropolitan regions. He found that generalized job dispersion was a more common spatial process than subcentering during the 1980s and 1990s. Importantly, however, he concluded that each metro area has a unique pattern of decentralization based on its history and context. For six metropolitan areas, three distinctive patterns of spatial development were identified. In Portland and Philadelphia, job dispersion was predominant, while polycentricity was reinforced in Los Angeles and San Francisco. New York and Boston were less prone to decentralization as a result of their large and well-established CBDs.

In one of and comprehensive studies, Arribas-Bel and Sanz-Gracia (2014) examined the urban spatial structure of 359 MSAs in 1990, 2000, and 2010. Their study had three key findings: (1) the monocentric structure persists in a majority of metropolitan areas, (2) the pattern of employment centers remains stable for most metropolitan areas, and (3) polycentric metro areas are larger and denser than monocentric areas, with higher per capita incomes and lower poverty rates. At first, Arribas-Bel and Sanz-Garcia's findings may seem to contradict previous studies that found that decentralization was an overwhelmingly common trend in US metropolitan areas. They found that 56.5% of MSAs were identified as monocentric in 1990 and that this number did not decline in 2010, rather stabilizing at 57.7%. However, Arribas-Bel and Sanz-Garcia only counted the *number* of centers and subcenters but did not measure the strength of the centers. In other words, if the *share* of employment in a CBD decreased for a given monocentric metropolitan area between 1990 and 2010, it cannot be detected in these authors' approach. To respond to this issue, a more nuanced understanding of metropolitan typology is needed, taking into account the share of regional employment contained in each center.

There are only few studies about the typology of MSAs based on spatial structure and decentralization pattern. One of the most comprehensive studies on this topic is by Cutsinger and Galster (2006). They investigated the spatial pattern of jobs and residential land uses for the 50 largest US urbanized areas in 1990. They used seven independent empirical factors (density, continuity, concentration, centrality, proximity, mixed use, and nuclearity) for their classification. Using cluster analysis, they proposed four distinctive groups of metropolitan regions. Type (1) is defined as deconcentrated, dense areas "intensively and continuously developed but without major clusters," and includes

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Boston, Denver, Detroit, Los Angeles, Miami, Minneapolis, San Diego, and San Jose. Type (2) comprises leapfrog areas defined as "highly concentrated pockets amid generally low density, discontinuous development," including Atlanta, Baton Rouge, Charlotte, Grand Rapids, New Haven, Philadelphia, and Pittsburgh. Type (3) refers to compact, core-dominant areas defined as "development with high proximity to the central nucleus, but only moderate density and continuity," including Las Vegas, New Orleans, and Washington DC. Type (4) is defined as dispersed area "development extending far from the core without notable concentrations or nuclei," and includes Baltimore, Buffalo, Cincinnati, Dallas, Houston, Indianapolis, Phoenix, Portland, St. Louis, Salt Lake City, and Seattle. We adopt Cutsinger and Galster's (2006) cluster analysis method to propose a new typology based on centralization and polycentricity indices.

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2.2. *Identifying employment centers*

Throughout this paper, we use "center" to mean either the main job center or a subcenter in a metro area. While some studies (Cervero & Wu, 1997; Giuliano & Small, 1991; McMillen & McDonald, 1998) had only two criteria (a minimum gross density of 10 employees per acre and minimum total employment of 10,000), others (Cervero, 1989; Garreau, 1991) had a long list of criteria for identifying centers, including such factors as employment size, office and/or retail space, commute flows, job-housing ratio, and land-use mix. Recent studies increasingly rely on employment density and related factors for defining centers (Lee, 2007). Cervero (1989) defined subcenters as "subcities" with similar densities and land-use mixtures of downtowns. South Coast Plaza in California and Post Oak Galleria in Texas are examples of such subcities. Garreau (1991) defined "edge cities" as emerging new centers far from the CBD. An edge city, according to Garreau (1991), has at least five million square feet of rental office/commercial space, at least 600,000 square feet of rental retail space, more jobs than bedrooms, is publicly perceived as a single place (has a distinct identity), and was nothing like a city 30 years ago. Tysons Corner, Virginia is the prime example of an edge city.

One of the most constraining features of the earlier models of urban centers is their reliance on an arbitrary definition of density or employment cutoff, which affects the number of subcenters that are found in the data (Anas et al., 1998). The other shortcoming of these models is the lack of generalizability of the subcenter threshold; finding appropriate cutoff values requires an extensive local knowledge of a city, narrowing the range of analytical possibilities. The thresholds for Manhattan, for example, are not the same as those for Salt Lake City. Finally, this method is not always able to find "clusters" of activities. In most cases the potential subcenters are several individual census tracts, which are distributed across a city without much notable influence on surrounding areas.

McMillen and Smith (2003), in a nonparametric procedure, identified all tracts with significantly positive residuals in a locally weighted regression (LWR) as potential employment centers. From these potential employment centers, they selected groups of tracts that were contiguous and had employment exceeding 10,000. Lee (2007) modified McMillen's (2001) method by using LWR with a less smoothed surface and

setting the minimum density cutoffs of each metropolitan area to the level of its 90-percentile employment density.

In a unique method, Yang et al. (2012) proposed a polycentricity measure for population centers. This method can be easily applied for job polycentricity as well. Yang et al. first calculated the average regional population density and population density for every census tract. They then divided the tracts into four groups: low density (below the average), moderate density (from average density to 5 times average density), relatively high density (from 5 times to 10 times average density), and high-density tracts (density higher than 10 times the average). They then calculated a directional distribution ellipse to characterize the spatial distribution of each density group using spatial statistics. They proposed two polycentricity indicators by dividing the area of the ellipse of high-density group by the ellipse of all tracts, and also by dividing the area of the ellipse of modest high-density group by the ellipse of all tracts. The primary weakness of this method is that the indices are sensitive to the presence of large, unpopulated tracts in outlying areas, which can unrealistically decrease the polycentricity measure and can erroneously identify centers as scattered units rather than clustered (since this method relies on the absolute value rather than the neighboring value).

In a different approach, researchers used spatial statistics tools to identify clusters with significantly higher employment density than their surrounding areas (Arribas-Bel & Sanz-Gracia, 2014; Baumont, Ertur, & Gallo, 2004; Guillain, Le Gallo, & Boiteux-Orain, 2006; Riguelle, Thomas, & Verhetsel, 2007). In this approach, high density clusters represent the concentration of employment relative to that of the surrounding areas. This approach is based on local spatial autocorrelation statistics (Local Moran's *I*) introduced by Anselin (1995). Similar to cutoff methods, spatial statistics approaches use threshold criteria. These approaches only require the analyst to choose the degree of significance and a neighborhood measure—these are not place-specific and thus have the advantage of not requiring comprehensive local knowledge.

Local Moran's *I* indicates the extent of significant spatial clustering of similar values around each observation and can be used to locate significant positive autocorrelation. Local Moran's *I* is defined as

$$I_i = \frac{(x_i - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2/n} \sum_{j=1}^{n} w_{ij} \sum_{j} w_{ij}(xj - \bar{x})$$

where I_i is the local Moran's *I* statistic, x is the value of the employment density, w_{ij} is the matrix of spatial weights, i corresponds to an observation unit and j to the length of the matrix and n is the number of observations. By calculating z-values of the local Moran statistics (see Anselin, 1995), it is possible to identify two types of spatial clusters and two types of outliers:

- High–high → High values around neighbors with high values (cluster)
- Low–low values around neighbors with low values (cluster)
- High–low → High values around neighbors with low values (outlier)
- Low–high → Low values around neighbors with high values (outlier)

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Another method for identifying employment centers is local Getis-Ord G_i^* statistic. The Getis-Ord G_i^* statistic calculates whether features with high values or features with low values tend to cluster in a study area. This analysis compares the sum value of neighbors of a certain point to the overall sum value of the study area. When the local sum (a feature's value and the values for all of its neighboring features) is much higher than the expected local sum, and that difference is too large to be the result of random chance, there is a statistically good chance that the feature is part of a hot spot.

The Getis-Ord G_i^* is defined as

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j}x_j - \bar{X}\sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{\left[n\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}}$$

where x_j is the attribute value for feature j, $w_{i,j}$ is the spatial weight between feature i and j, n is equal to the total number of features, and

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\bar{X})^2}$$

Both Local Moran's I and Getis-Ord G_i^* methods have been used in many previous studies (Baumont et al., 2004; Guillain et al., 2006; Arribas-Bel and Sanz-Gracia, 2014; Paez, Uchida, and Miyamoto, 2001; Feser, Sweeney, and Renski, 2005; Asikhia and Nkeki, 2013). Their results can be similar in some cases, but there is one important difference between the two: Moran's I can differentiate between cases of positive (HH, LL) and negative (HL, LH) spatial autocorrelation, while the Getis-Ord can only identify cases with positive autocorrelation.

Table 1 presents the summary of nine different methodologies for identifying employment centers. The wide range of methods shows that a shared definition of employment centers does not exist. Employment centers can be identified: (1) relative to an absolute cutoff value, (2) relative to the average density, (3) relative to their immediate neighborhood, (4) relative to the distance from CBD, and (5) any combination of the other four criteria. None of the methodologies is essentially better than the rest. At the end, the choice of methods should be determined by the purpose of the research.

3. Methods

3.1. *Sample*

In this study, we analyzed 356 MSAs in the lower 48 states of the United States. A metropolitan area is a region that consists of a densely populated urban core and the less-populated surrounding territories to which it is economically and socially linked. In 2010, 19 metropolitan areas of our sample had a population of more than two million

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Table 1. Summary of literature on identifying employment centers.

Methodology	Description	Selected papers	Main criticism
Total employment levels and employment density cutoffs	D–E centers D = jobs per acre E = total Jobs 10–10 and 20–20 centers are the most common thresholds; e.g. 20 jobs per acre and 20,000 jobs	Giuliano and Small (1991); Giuliano et al. (2007)	Defining a threshold is subjective and cutoffs appropriate for one city/region may not be relevant for another
Employment-to-population (or resident worker) ratio and total employment	Center has a higher proportion of employment to population than the average of the city/region, with at least 7,000 jobs	Boiteux-Orain and Guillain (2004)	Same as above
Relative to the average density cutoffs	Center has a density higher than 10 times the average	Yang et al. (2012)	Same as above; also, it is sensitive to the presence of large, unpopulated tracts in outlying areas
Spline quantiles	Estimates the upper quantile employment density function of log employment density conditioned on a given distance from the CBD	Craig and Ng (2001)	The procedure is detecting rings of high density rather than actual centers; also, employment centers will be dependent on distance to the CBD
Locally weighted regression (LWR) and total employment cutoffs	Identifies subcenters as local peaks in the predictions from nonparametric regressions of the natural logarithm of employment density on distance from the CBD (the centers are outliers relative to a spatial average that uses half of all the observations); total employment exceeds 10,000	McMillen (2001); McMillen and Smith (2003); McMillen (2004)	Employment centers will be dependent on distance to the CBD—therefore, conformity to the traditional model of a monocentric region is critical
LWR with small subsamples	Identifies candidate centers by LWR with a small window. For each candidate center, the process is repeated locally, using LWR. The centers are outliers relative to their immediate neighborhood.	Redfearn (2007)	More locations (with lower employment density) will be identified as subcenters in outlying areas.
Kernel estimation and *K*-function estimation	Input = census tracts as a point pattern, weighted by the number of employments Output = a continuous surface that provides the intensity of jobs	Maoh and Kanaroglou (2007); Maoh, Koronios, and Kanaroglou (2010)	Kernel maps are raster files and their unit of analysis is a predefined pixel grid, not a geographical unit such as block-groups; therefore, the boundaries of centers cannot precisely be defined
Cluster and outlier analysis (Local Moran's *I*)	Identifies concentrations of high values, concentrations of low values, and spatial outliers (applied on employment density or employment-to-population ratios)	Baumont et al. (2004); Guillain et al. (2006); Arribas-Bel and Sanz-Gracia (2014)	Employment centers will be dependent on the average employment density of the study area; therefore, the complexity of larger metropolitan areas cannot be captured
Hot spot analysis (Getis-Ord G_i^*)	Identifies the location of high value clusters by assessing each unit within the context of neighboring units and comparing the local values to the global values	Paez et al. (2001); Feser et al. (2005); Asikhia and Nkeki (2013)	Same as above

people. Thirty-one MSAs had a population between 1 and 2 million, and 53 MSAs had a population between 0.5 million and 1 million. Finally, 145 MSAs had a population of less than 200,000 people.

3.2. *Data and variables*

The database for measuring the centralization and polycentricity indices consists of a combined file from two different data sources for each individual MSA: 2010 Longitudinal Employer-Household Dynamics (LEHD) on employment data at the block level and 2010 Census data on population at the block group level. We aggregated LEHD employment data to the block group level via ArcGIS; this was used as the unit of measurement. We also obtained metropolitan area and census block group boundary geometry data for 2010 from the Topologically Integrated Geographic Encoding and Referencing (TIGER) in ESRI shapefile format.

3.3. *Analytical methods*

Our methodology for proposing the US metropolitan typology has three main phases: (1) identifying centers; (2) measuring centralization and polycentricity indices; (3) proposing a new typology for the spatial structure of employment in the US metropolitan areas. In phase 1, our approach is using local statistics to identify the location of significant local clustering of employments. In phase 2, we measure the extent of centralization and polycentricity for 356 MSAs using 12 indices based on our findings in phase 1. In phase 3, cluster analysis is used to categorize MSAs based on their centralization and polycentricity degree.

3.3.1. *Phase 1: identifying centers*

As Table 1 presents, there are different methodologies for identifying employment centers. We applied a modified version of a methodology that could best answer our research question: "What is the typology of US metropolitan areas?" If we want to know whether traditional CBDs are still the dominant feature in the current spatial structure of all metropolitan areas, or whether more competing centers have emerged, job centers should be defined as clusters of high density employment regardless of CBD location. The classic model of a region with a dominant center could not be applied to all cases in our data. Therefore, LWR was not an appropriate method for this study.

In addition, we decided not to use LWR because several statistical problems are often associated with this method, such as cases with extreme coefficients, poor fitting local models, and multicollinearity. Studies such as McMillen (2001) and Lee (2007) cover less than 10 MSAs, so it was practical to conduct different diagnostic procedures for those cases. Since we are studying 356 MSAs we had to choose a technique with fewer diagnostic procedures.

Given that our sample includes a wide range of MSAs, we did not use an absolute value as a cutoff for potential centers. In other words, total employment density of 10 jobs per acre or total employment of 10,000 jobs (Giuliano & Small, 1991; Lee, 2007; McMillen & Smith, 2003) is a high cutoff number for most medium-sized and small MSAs. Therefore, we applied nonparametric methods to locate clusters of high

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employment density relative to the average value of any given MSA; then we set a low cutoff value (2.5 jobs per acre) to select final centers. Our method, similar to McMillen and Smith (2003) and Lee (2007), is a two-step process, but we were more conservative on our nonparametric section (step one) and more relaxed on our absolute value cutoff (step two).

For the nonparametric analysis we use Getis-Ord G_i^* instead of Local Moran's I because we were interested in all clusters of high values, not only high values surrounded by high values. The analysis was done on a one-by-one basis for all MSAs. Getis-Ord G_i^* also requires certain diagnostic procedures. The most important is identifying the presence of "overlapping subsets" in local statistics because the data used to produce a local statistic at location i is also used to produce the statistics at location j. Therefore, these two statistics are not independent. However, we can assume independence when we derive their variances. Different adjustment techniques can be used to conservatively account for overlapping subsets. False discover rate (FDR) adjustment has been used for this study. FDR procedures are designed to control the expected proportion of incorrectly rejected null hypotheses or "false discoveries." FDR consists of three steps: (1) order the test statistics p-values in ascending order, (2) find P_{critical} as the first p-value which is smaller than PFDR = rank number divided by the number of cases multiplied by $a = 0.05$, and (3) regard all tests as significant for which $P_i \leq P_{\text{critical}}$. Through taking these steps, we set a unique confidence interval for each MSA based on FDR adjustment.

3.3.2. *Phase 2: centralization and polycentricity indices*

Centralization and polycentricity (or concentration) are two urban spatial dimensions in urban form studies (Anas et al., 1998; Galster et al., 2001; Lee, 2007). Centralization is the extent of employment concentration near the CBD and polycentricity measures the degree of employment clustering around few locations. For this study, we adopt the conceptual framework of polycentricity degree proposed by Yang et al. (2012). The advantage of this method is that the polycentricity measure is sensitive to the distance of employment clusters from the CBD, while previous methods were not. Figure 1 compares different scenarios of polycentricity. In a typical monocentric situation, block groups with high employment density are close to the CBD. In Figure 1(a), Scenario B represents a more concentrated distribution of employment than Scenario A. In other words, Scenario B has the higher centralization degree than Scenario A.

For polycentricity degree, we quantify the location, the number, and the size of high-density nodes. The higher the penetration of the high-density nodes into the suburban area, the higher the polycentricity score. For example, Figure 1(c) represents higher polycentricity than Figure 1(b), as the number of suburban nodes has increased. Figure 1(d) also suggests relatively higher polycentricity than Figure 1(b) because the outward shift of the higher density nodes tends to increase accessibility of the latter in the suburban area. Figure 1(e) represents higher polycentricity than Figure 1(d) because the suburban nodes have become stronger (Yang et al., 2012, p. 199).

To calculate centralization and polycentricity indices, we had to differentiate the main centers or CBDs from other subcenters. Therefore, we relied on three spatial elements of urban form: *Center, Main Center*, and *Central Core*. Figure 2 shows the

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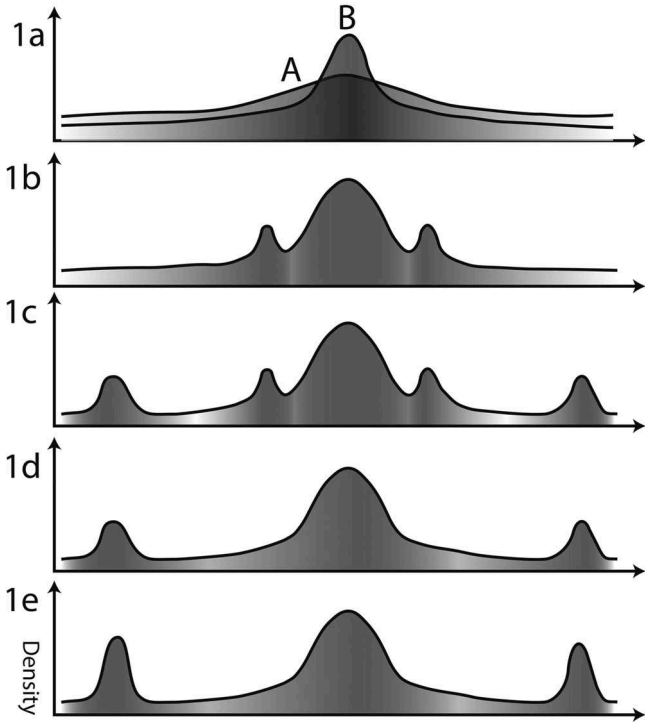

Figure 1. Conceptualizing polycentricity, adopted from Yang et al., 2012, p. 199.

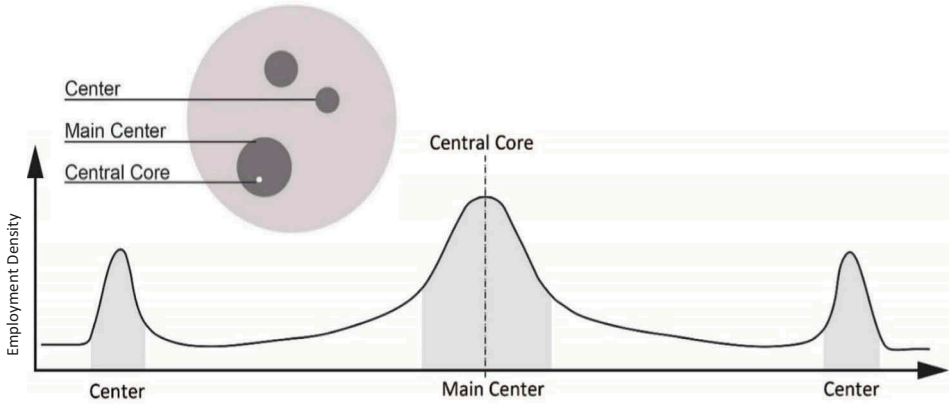

Figure 2. Illustration of center, main center, and central core. Source: authors.

relationship of these three spatial elements. *Main Centers* are similar to CBDs, but since our sample includes small- and medium-sized MSAs, no census data is available for the location of their CBDs. The most recent index of CBDs, as published by the US Census Bureau, is from 1983. This data is now more than 30 years old and captures CBDs for only 232 large MSAs. Thus, we decided to measure *Central Cores* in order to capture the cores of MSAs without indexed CBDs (142 MSAs). We defined *Central Core* for

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Table 2. Methods used to locate spatial elements of urban form.

Spatial element	Method used
Center	Census blocks with significant G_i^* values of employment density compared with the surrounding 1-km (0.62 mile) radius and employment density higher than 2.5 jobs per acre
Main center	The center that has the central core within its boundary
Central core	Census block with the highest Moran's *I* value of employment density within a 2-km (1.24 mile) radius

each MSA as the census block that has the highest Moran's *I* value of employment density within a 2-km radius (1.24 miles).

Identifying *Central Cores* helps us distinguish each MSA's *Main Center* from other centers. In other words, *Main Center* is a center that contains *Central Core*. We used the Getis-Ord G_i^* for identifying all possible centers and the Local Moran's *I* to find the Central Core (see Table 2). We could have simply considered the center with the highest employment or employment density as the main center. However, after comparing both techniques, we were convinced that *Central Core* can better identify the location of CBDs. We validated the results with a 1983 census shapefile of CBDs (sample size 247 MSAs) on the assumption that the location of CBDs has not changed much since 1983. We found that the result of the local Moran's *I* with a weighting matrix of 2 km (1.24 mile) had the best matches with the 1983 shapefile of CBDs. We found that more than 90% of census block groups we identified as *Central Core* were located within the 1983 CBD boundaries.

We operationalized centralization and polycentricity using multiple indices. Tables 3 and 4 describe these indices and their computation process. We used principal component analysis (PCA) to reduce all listed indices into two centralization and polycentricity indices. PCA is a statistical technique used to extract one or more common underlying factors from a large number of correlated variables. The extracted factors, or principal components, are weighted combinations of the correlated variables. The higher the correlation between a variable and a principal component, the greater the loading and the more weight the original variable is given in the overall principal

Table 3. List of centralization indices.

Centralization indices	Computation process
Strength of the main job center	Ratio of total employment in the main job center to total employment within each MSA
Degree of monocentricity	Ratio of total employment in the main job center to total employment within all job centers
Concentration of population around the main job center	Share of overall metropolitan area population within a 5-mile radius around the main job center
Nuclearity of the main job center	Job density of the main employment center divided by the average job density of all urbanized areas in each MSA
Normalized weighted average distance from the central core	Weighted average distance of all block groups from the central core divided by the average distance of all block groups from the central core (weighting is the share of metro employment in any given census block-group)

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Table 4. List of polycentricity indices.

Polycentricity indices	Computation process
Strength of job subcenters (I)	Ratio of total employment in all subcenters to the total employment within each MSA
Strength of job subcenters (II)	Ratio of total employment in all job subcenters to the total employment within all job centers (subcenters + main center)
Concentration of population around job subcenters	Share of overall MSA population within a 5-mile radius of the job subcenters
Nuclearity of the job subcenters (I)	Weighted average job density of subcenters divided by the average job density of all urbanized areas for each MSA
Nuclearity of the job subcenters (II)	Weighted average job density of subcenters divided by the weighted average job density of all job centers of for each MSA
Degree of distanced centers (I)	Weighted average distance of all block groups within subcenters from the central core, divided by the average distance of all block groups from the central core (weighting is the share of metro employment in any given census block-group within subcenters)
Degree of distanced centers (II)	Weighted average distance of all block groups within subcenters from the central core, divided by the average distance of all block groups from the central core (weighting is the share of all centers' employment in any given census block-group within subcenters)

component score. The greater the correlation between the original variables, the more variance is captured by a single principal component.

3.3.3. *Phase 3: proposing a new typology*

Based on centers identified in phase 1, we can divide all metropolitan regions into three categories: (1) MSAs without any significant center (generalized dispersion), (2) MSAs with a main center and without any significant subcenter (monocentric), and (3) MSAs with both significant main center and subcenters (polycentric). However, the boundary between these urban form types is not discrete. For example, no MSA exists in the real world with an ideal type of monocentricity. Even the most monocentric MSA has some degree of job dispersion or job clustering outside its CBD. Given this reality, to what formal type should a metropolitan area with a weak CBD belong? Is it monocentric or dispersed? What about a metropolitan area with a weak center and weak subcenters? In fact, most MSAs have some characteristics of all three categories. To represent the overlapping tendencies of these three formal types, we created three additional hybrid types and categorized each MSA into one of our six categories. Figure 3 illustrates the relationship of these six types. Three types (b, d, and f) reflect the most pure forms of *monocentric, polycentric*, and *dispersed*. The other three categories share characteristics of two types; a: *Centralized-dispersed* (monocentric—generalized dispersion), c: *Centralized-polycentric* (polycentric—monocentric), and e: *Dispersed-polycentric* (generalized dispersion—polycentric).

We use cluster analysis to operationalize this classification based on the centralization and polycentricity indices explained above. Accordingly, *centralized-dispersed* MSAs obtain a low centralization score and a (near) zero score for polycentricity, while *Monocentric* MSAs obtain a high centralization score and a (near) zero score for polycentricity. *Centralized-polycentric* MSAs obtain a high centralization score and a low score for polycentricity. *Polycentric* MSAs obtain a low centralization score and a high score for polycentricity. *Dispersed-polycentric* MSAs obtain low centralization and

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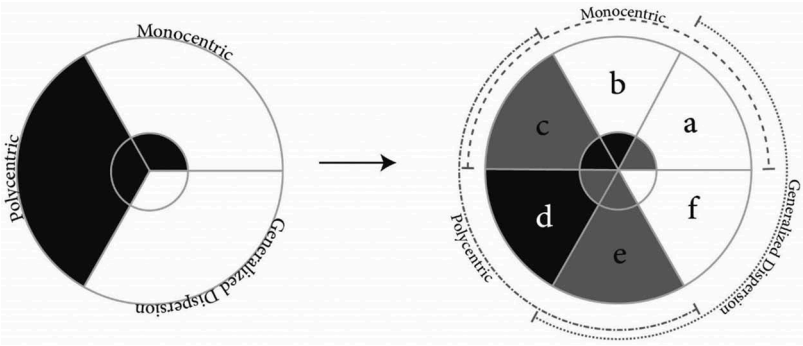

Figure 3. Conceptualizing the typology of metropolitan form; white areas represent lack of any significant center, gray areas represent the presence of weak centers, black areas represent the presence of strong centers. Source: authors.

polycentricity scores. And finally, *Dispersed* MSAs obtain zero scores for both centralization and polycentricity indices.

4. Results

4.1. *Significance of employment centers in urban geography of United States*

Table 5 presents an overview of job and population shares in employment centers in 2010. Around 18.4% of overall employment in all metropolitan regions for this year is located in job centers. This is a significant proportion considering the fact that employment centers occupy only 0.15% of MSAs overall. Main centers have two times more jobs than subcenters. The average employment density of job centers for the United States as a whole is 31 per acre. The average job density of main centers is 36.4 per acre, while the average job density of subcenters is 23.5 per acre.

The share of total metropolitan population within job centers is less than 3%. The average population density of job centers is 10.3 per acre. For main centers, this number is 11.6 per acre and for subcenters it is 8.5 per acre. Within a 5-mile buffer around main centers, the population share will increase from 1.7% to 21.1%. Within a 5-mile buffer around subcenters, the population share will increase from 0.9% to 27.7%. This shows that, despite the relatively low share of population in job centers, proximity of population to both main and subcenters tends to be relatively high. Figures 4 shows the location of employment centers and the main center in four MSAs: Lansing, Michigan, Philadelphia, Detroit, and Los Angeles.

Table 5. Descriptive statistics of 2010 employment centers.

	Number of centers	2010 Employment share		2010 Population share		2010 Land area share (total in square mile)	
Main center	349	1,3307,997	12.6%	4,255,354	1.7%	571	0.1%
Subcenters	537 (In 224 MSAs)	6,095,209	5.8%	2,199,253	0.9%	404	0.05%
All centers	886	19,403,206	18.4%	6,454,607	2.6%	975	0.15%

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Table 6. Component matrix of centralization.

Centralization variables	Factor loading
Strength of the main job center	0.710
Degree of monocentricity	0.636
Concentration of population around the main center	0.698
Nuclearity of the main job center	0.802
Normalized weighted average distance	0.467
Total percentage of explained variance	43%

Table 7. Component matrix of polycentricity.

Polycentricity variables	Factor loading
Strength of the job subcenters (I)	0.812
Strength of the job subcenters (II)	0.829
Concentration of population around subcenters	0.772
Nuclearity of the job subcenters (I)	0.835
Nuclearity of the job subcenters (II)	0.836
Degree of distanced centers (I)	0.921
Degree of distanced centers (II)	0.907
Total percentage of explained variance	45%

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4.2. *Centrality and polycentricity measures*

To calculate the centralization and polycentricity indices, we conducted a PCA on the measured variables from phase 2. The principal component that captured the largest share of common variance among the measured variables was selected to represent the index. Factor loadings (the correlation between a variable and a principal component) and percentages of explained variance are shown in Tables 6 and 7.

For the centralization index, the first component explained 43% of variations among the five variables and, as expected, all five component variables load positively on the centralization factor. Thus, for all component variables, higher values translate into higher centralization scores.

We ran another PCA on seven measured variables from phase 2 to extract the polycentricity index. The first component explained 45% of variance between the seven component variables. Again, all component variables load positively on the polycentricity factor, which means higher component values translate into higher polycentricity scores.

4.3. *Typology of American metropolis*

Similar to Cutsinger and Galster (2006), we used cluster analysis to propose a new typology for the spatial structure of employment in metropolitan regions, based on the generated centralization and polycentricity indices. Table 8 presents the results of our cluster analysis. With regards to the centralization and polycentricity measures, we matched each group of MSAs to one of the six types discussed in Figure 3. Out of 356 MSAs, *centralized-dispersed* is the most common type, with 130 MSAs. *Polycentric-dispersed* is the second most common type, with 113 MSAs. Forty-five and 44 MSAs belong to *polycentric* and *centralized-polycentric* types, respectively. Only six MSAs have no significant center and classified as *dispersed* type. The *monocentric* type is also low in number, with just 18 MSAs. As we discussed earlier, due to the overlapping properties of these categories, we summed up the frequency of similar

Table 8. Result of cluster analysis: frequency and properties of each type.

	Type	Centralization value (0–100)	Polycentricity value (0–100)	Frequency
a	Centralized-dispersed	57	0	130
b	Monocentric	79	0	18
c	Centralized-polycentric	47	21	45
d	Polycentric	19	58	44
e	Dispersed-polycentric	34	36	113
f	Dispersed	0	0	6

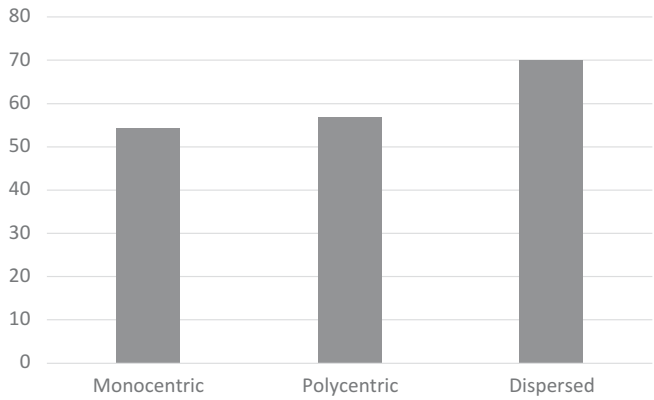

Figure 4. Percentage of MSAs with monocentricity, polycentricity and dispersion characteristics.

types based on monocentricity, polycentricity and dispersion measures in order to get a more holistic picture of metropolitan-scale urban form in the United States. Figure 4 shows the percentage of MSAs sharing one of the three mentioned spatial characteristics. Dispersion is the most common spatial characteristic in US metropolitan regions. Employment dispersion is the dominant spatial characteristic in almost 70% of MSAs. More than half (54%) of the MSAs present some degree of monocentricity in their spatial structure, and 57% of MSAs present some degree of polycentricity. Figure 5 shows MSAs that represent each of the six types.

Table 9 shows the top five most populated MSAs in each category. For example, the Chicago MSA has both center and subcenters. But less than 1% of its total employment is located in the subcenters. 15% of total employment was located in the CBD, which is a little more than the average share of CBDs for all MSAs. The Chicago MSA has weak subcenters and a moderate main center, which are the characteristics of the centralized-dispersed type. On the other hand, in the Los Angeles MSA, almost 13% of the total employment was located in the subcenters, with only 6% in the main center. Such a moderate main center and strong subcenters are the characteristics of the polycentric type. Although some studies have categorized Chicago as a polycentric region (e.g. McDonald & Prather, 1994; McMillen & McDonald, 1998; McMillen & Smith, 2003), and some studies identified many more subcenters for the Los Angeles MSA (e.g. Giuliano et al., 2007; Redfearn, 2007), this dissimilarity can be explained by the different methods that have been applied for identifying employment centers (as explained in Table 1). While, similar to the present study, "distance from CBD" was not a criterion in many analyses (e.g. Arribas-Bel & Sanz-Gracia, 2014; Baumont et al., 2004; Guillain

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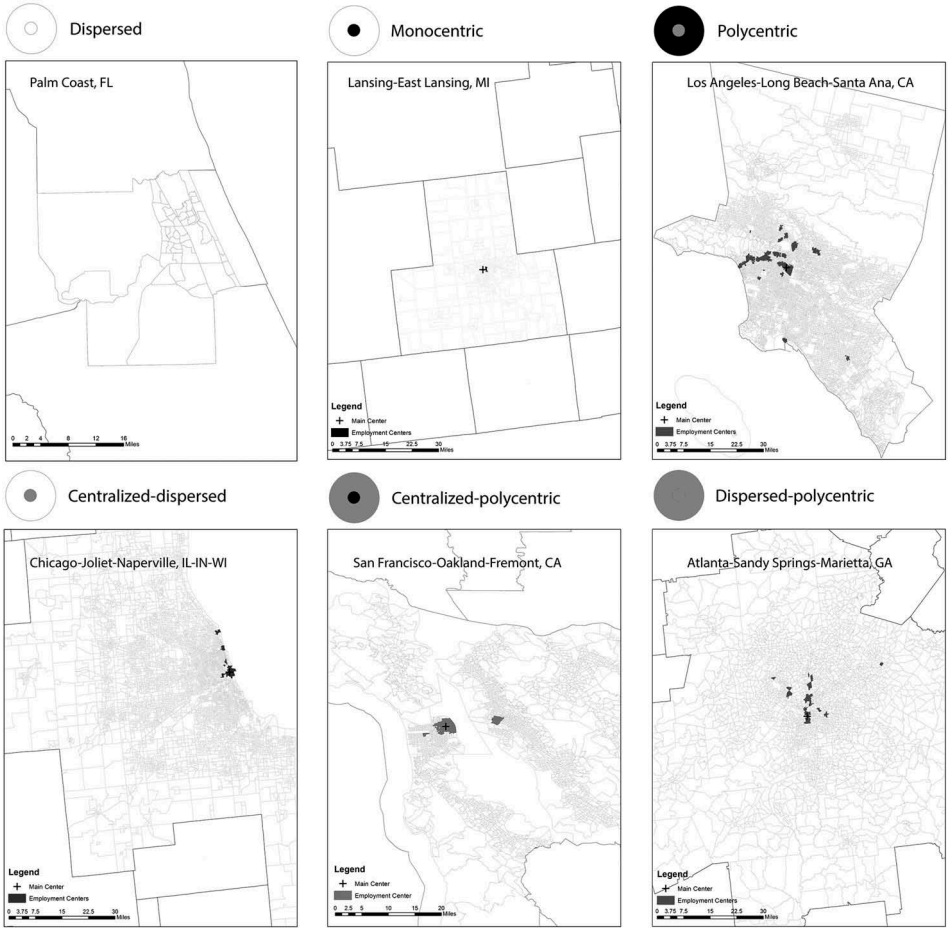

Figure 5. The employment centers and the type of six US metropolitan areas. Source: authors.

et al., 2006; Riguelle et al., 2007), those which adopted this criterion generally identified more employment centers (McDonald & Prather, 1994; McMillen & McDonald, 1998; McMillen & Smith, 2003; Redfearn, 2007). For example, in an area with high average density such as the Los Angeles region, one would expect an employment cluster with very high density. However, Redfearn (2007) has identified centers with density as low as 3.3 jobs per acre in Los Angeles region, while the median tract employment density in the sample is also 3.3 jobs per acre. In summary, employment centers in this study are mainly dependent on the average employment density of the study area, not the immediate neighborhood nor the study areas' distance to CBD.

Figure 6 shows the centralization and polycentricity scores of the five most populated MSAs in each category. This figure shows that Los Angeles, New York, and Philadelphia are more polycentric; New York, Chicago, and Lansing are more monocentric; and finally, Anchorage, Philadelphia, and Chicago are more dispersed than the three other regions.

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Table 9. Top five most populated MSAs in each type.

Centralized-dispersed	Monocentricity	Centralized-polycentric	Polycentricity	Dispersed-polycentric	Dispersed
Chicago–Joliet–Naperville, IL–IN–WI	Lansing–East Lansing, MI	New York–Northern New Jersey–Long Island, NY–NJ–PA	Los Angeles–Long Beach–Santa Ana, CA	Philadelphia–Camden–Wilmington, PA–NJ–DE–MD	Anchorage, AK
Las Vegas–Paradise, NV	Champaign–Urbana, IL	San Francisco–Oakland–Fremont, CA	Dallas–Fort Worth–Arlington, TX	Houston–Sugar Land–Baytown, TX	Palm Coast, FL
Charlotte–Gastonia–Rock Hill, NC–SC	Gainesville, GA	Denver–Aurora–Broomfield, CO	Miami–Fort Lauderdale–Pompano Beach, FL	Washington–Arlington–Alexandria, DC–VA–MD–WV	Mankato–North Mankato, MN
Milwaukee–Waukesha–West Allis, WI	Springfield, IL	Portland–Vancouver–Hillsboro, OR–WA	Detroit–Warren–Livonia, MI	Atlanta–Sandy Springs–Marietta, GA	Fairbanks, AK
Jacksonville, FL	Athens–Clarke County, GA	Sacramento–Arden–Arcade–Roseville, CA	Riverside–San Bernardino–Ontario, CA	Phoenix–Mesa–Glendale, AZ	Carson City, NV

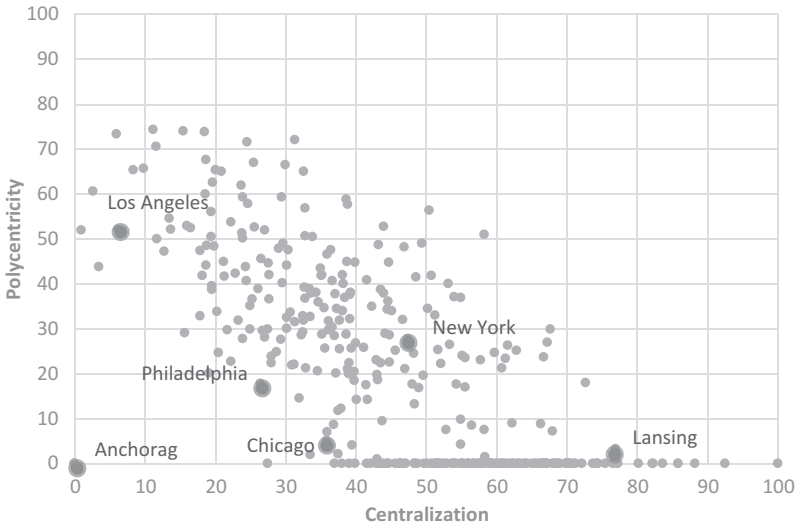

Figure 6. Scatter plot of centralization and polycentricity degree of six MSAs representing six types, and other MSAs.

4.4. *The average population size and density of each type*

In order to understand the distribution of our proposed typology according to small, medium-sized, and large metropolitan areas, we computed the mean and standard deviation of population size and density of each type (Table 10). We decided to drop the *dispersed* category in this step because of the low number of observations (only six MSAs fall into this category). The result shows that there are meaningful differences between categories in terms of their average population size and density. Figure 7 ranks five types according to their average population size and density. It shows that the majority of MSAs with medium-sized population are either centralized-dispersed or dispersed-polycentric.

We conducted the analysis of variance (ANOVA) test and post-hoc test in order to analyze the differences between group means in terms of both population size and density. Results show that *polycentric* MSAs have significantly higher population and density means than both *monocentric* and *centralized-dispersed* MSAs. In addition, they

Table 10. The mean and standard deviation of population size and density of US metropolitan areas, categorized by type.

	Population size		Population density per square mile	
Type	Mean	Standard deviation	Mean	Standard deviation
Polycentric	1,115,229	228,675	888.7	809.7
Centralized-polycentric	993,609	2,851,316	705.1	590.1
Dispersed-polycentric	854,535	1,225,186	657.9	398.6
Centralized-dispersed	348,091	859,229	540.4	316.7
Monocentric	150,362	74,445	470.8	133.3
All types	673,053	1,579,510	639.1	473.7

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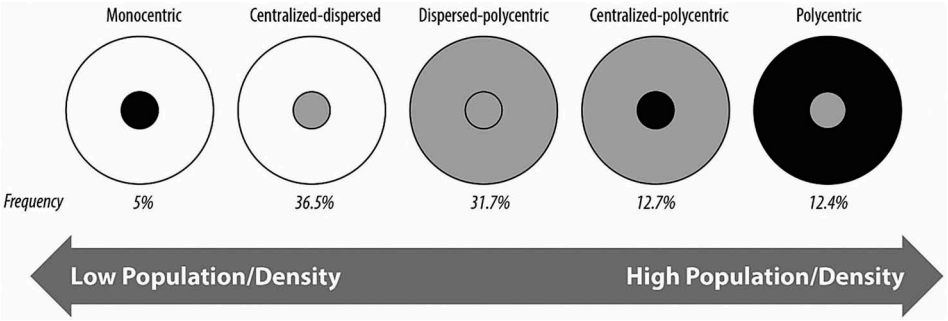

Figure 7. Ranking types according to their average population size and density.

have significantly higher population density means (and not size) than *dispersed-polycentric* MSAs. In addition, *centralized-dispersed* MSAs have significantly population and density means than both *dispersed-polycentric* and *centralized-polycentric* MSAs. Finally, *monocentric* MSAs have significantly lower population size and density means than *centralized-polycentric* MSAs (see Figure 8).

5. Conclusion

We have quantitatively investigated the 2010 spatial structure of employment in 356 US MSAs and have located main job centers/CBDs and all significant subcenters. We computed centralization and polycentricity indices based on the location and employment totals of job centers. These indices were extracted from 12 measured variables using principal component analysis. We then created a classification for metropolitan regions based on proprieties of monocentricity, polycentricity, and dispersion. Finally, we used cluster analysis to categorize metropolitan regions into six types based on their centralization and polycentricity scores. These categories include *centralized-dispersed, monocentric, centralized-polycentric, polycentric, dispersed-polycentric*, and *dispersed*.

Unlike some previous studies (e.g. Anas et al., 1998; Gordon & Richardson, 1996), we found that, compared to subcenters, main centers still play the key role in employment clustering. In general, 12.6% of jobs are located in the main centers, while only 5.8% of jobs are located in the subcenters. We also found that, despite the low population share of job centers, proximity of population to job centers is still critical in the spatial structure of the US metropolitan regions. In terms of typology, monocentric dispersion is the most frequent type, with 130 MSAs, followed by polycentric dispersion, with 113 MSAs. In general, and consistent with our literature review, dispersion is the most common characteristic among metropolitan regions. Job dispersion is a dominant spatial characteristic in almost 70% of MSAs. We found that polycentricity, with its 56.7% share, is a slightly more common spatial structure than monocentricity, with a 54.2 % share.

This study is one of the first attempts at the national scale to identify the location of CBDs and employment subcenters. We also propose a new typology for US metropolitan regions. Our results suggest that *generalized dispersion* is the most common spatial structure of US metropolitan regions and that purely monocentric or centralized-

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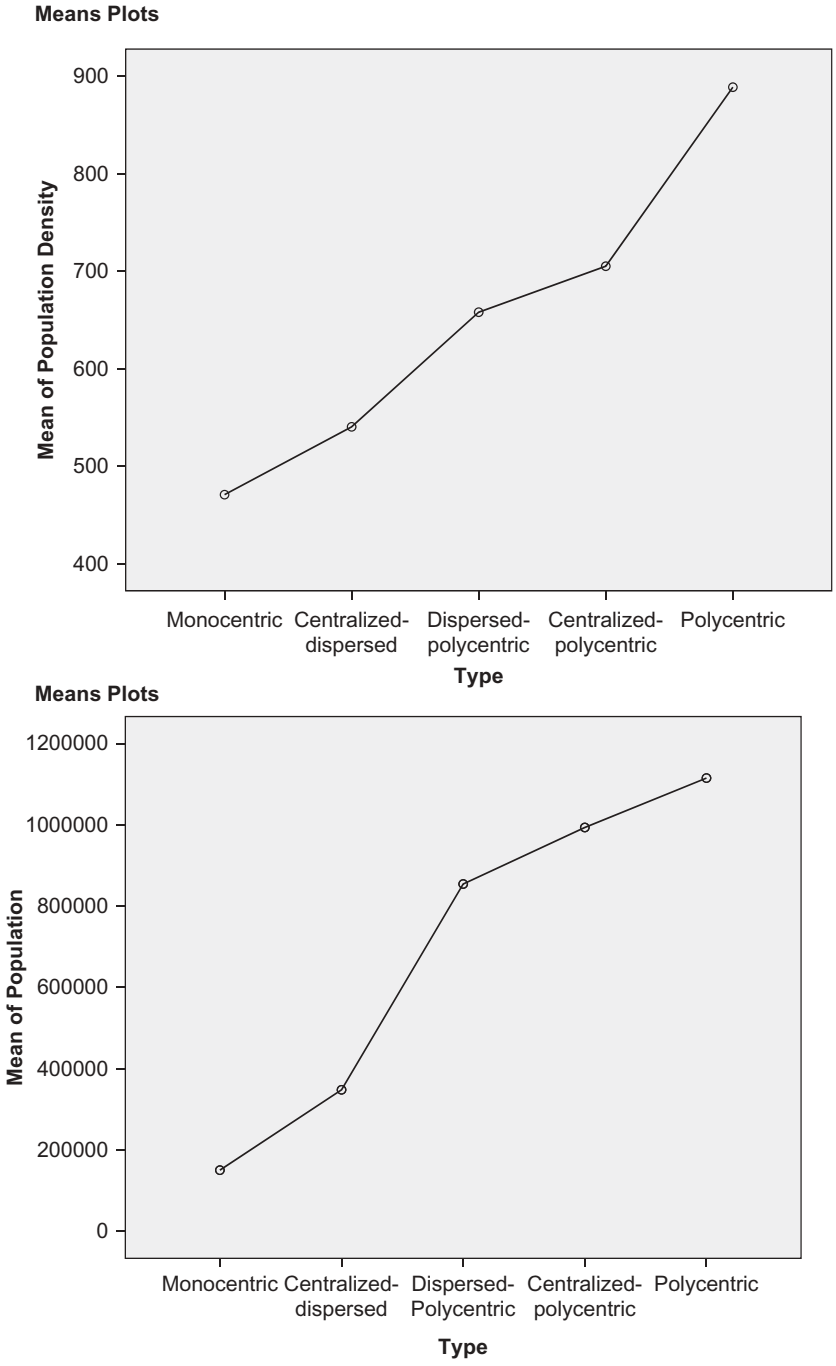

Figure 8. Mean of population density (top) and size (bottom) in each metropolitan type.

dispersed MSAs are mostly small. The more populated MSAs generally show some degree of polycentricity, and medium-sized MSAs are generally more dispersed than small and large MSAs. Investigating the causes of different spatial structure patterns for

metropolitan regions is not within the scope of this study, and more detailed case study analyses are needed to provide an in-depth understanding of why some metropolitan regions are more dispersed than others.

Before concluding, we must acknowledge a limitation of this study. In identifying CBDs, we were not able to take traffic flow into account. Traffic flow is one of the criteria for CBD identification by in the 1983 census, the last systematic identification of business districts at the national scale. The census defined CBDs as "an area of very high land valuation characterized by a high concentration of retail businesses, service businesses, offices, theaters, and hotels, and by a very high traffic flow," which could be comprised of one or multiple census tracts. Although we acknowledge its importance, we are not able to control for traffic flow due to a lack of data availability on this variable at the national scale. Consequently, the proposed typology is based solely on the spatial structure of employment in metropolitan areas.

The proposed typology can provide a theoretical framework for future studies at a regional scale, such as the impact of spatial typology on travel behavior, housing affordability, percentage of population below the poverty line, or unemployment rate. Although a range of built environment, socioeconomic, and demographic factors may have a stronger impact on these outcome variables, the spatial typology may also have significant impact after controlling for other influential factors. For example, it is clear that travel behavior in a small monocentric metro area is entirely different from that in a large monocentric metro area; however, after controlling for metropolitan population size or density we may find significant associations between monocentricity and a range of travel behavior characteristics, such as commuting time, commuting with public transportation or walking to work. Exploring this research area, for example, could direct regional planners and policy makers towards solutions for these regional issues.

While the focus of the paper is on the United States, the findings may shed light on the wider debate about metropolitan form in other countries. For example, in the case of Canada, Maoh et al. (2010) report that while Hamilton, Ontario has been sprawling for decades, polycentric characteristics have been emerged in recent years. In addition, Shearmur et al. (2007) examined the employment structure of Toronto, Montreal, and Vancouver in 1996 and 2001. They observed a dynamic process of growth and decline throughout metropolitan areas at a fine spatial scale. However, at a broader scale, employment was tending to grow in employment zones and there was no evidence of generalized dispersion. Studies such as these can affirm the association of metropolitan size and its spatial structure and explain why medium-sized MSAs are generally more dispersed than small and large MSAs. In this view, employment dispersion or sprawl can be better understood or managed as a transitional step from a monocentric to a polycentric urban form in the long run. In such a transition, policy interventions such as the imposition of congestion and emission fees for automobile use, or more proactive local planning to encourage compact, mixed-use development, can be considered as catalyzers for the evolution of urban form.

We end by re-acknowledging a limitation of this study: the conceptualization of the employment center itself. As we discussed in the literature review, at least nine different methodologies for identifying employment centers have been suggested in previous studies. If we had used a LWR method, for example, our study would have identified more small and relatively low density subcenters. However, we posit that even by

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applying the LWR method, the main findings of this study would be similar, given that our proposed typology is based on the strength of employment centers, not just their number.

Disclosure statement

No potential conflict of interest was reported by the authors.

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