U.S. METROPOLITAN SPATIAL STRUCTURE AND EMPLOYMENT GROWTH

A Dissertation

by

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ABSTRACT

This study explores the influence of US metropolitan spatial structure evolution on regional employment growth rate. The first part of this study investigates the evolution of US metropolitan spatial structures from 2000 to 2010. At the macro level, I categorized metropolitan areas (metros) into three groups (i.e., monocentric, polycentric, and coreless) based on the number of employment centers these metros had in 2000 and 2010. At the micro level, I sub-grouped the three macro spatial structure groups into micro-level clusters based on each metro's rank of employment shares in five sub-metro locations: the main-center, sub-centers, non-center clusters, non-cluster urban areas, and rural areas. The results show that (1) among 361 US metros, over 80 percent of metros remained in their original macro spatial structure type, and (2) less than 10 percent of metros experienced employment decentralization.

The second part of this study explores the influence of spatial structure evolution on regional growth rate. At the macro level, a series of two-sample t-tests showed that the group of monocentric metros that remained monocentric had no significant difference in employment growth rate from the group of monocentric metros that evolved to be polycentric. Conversely, the group of polycentric metros that remained polycentric had a higher employment growth rate than the group of polycentric metros that evolved to be monocentric. At the micro level, a regression analysis showed that the initial sub-centers' employment share had a larger positive effect on regional employment growth rate than the initial main-center employment share, while the

change in non-cluster urban areas' employment share had a larger negative effect on regional employment growth rate than the change in the non-center clusters' employment share.

The main conclusions from this dissertation are that (1) employment decentralization from the main-center to sub-centers increases regional employment growth rate, whereas employment dispersion — employment migration from centers (i.e., main-center and sub-centers) to non-centers (i.e., non-center clusters, non-cluster urban areas, and rural areas) – decreases regional employment growth rate, and (2) metros' macro and micro spatial structure types were relatively stable over the study period.

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CHAPTER I

INTRODUCTION

1.1 Background

The United States (US) has undergone rapid urban expansion during the last 50 years. Metropolitan areas (metros) have expanded across the landscape, resulting in structural changes. Numerous studies have focused on the causes and consequences, along with the costs and benefits, of urban expansion. However, certain important questions remain unanswered, such as: Are there patterns of urban expansion? Do all metros evolve from monocentric (i.e., with one employment center) to polycentric (i.e., with more than one employment center)? What are all of the possible evolution paths? How do different evolution paths affect regional employment growth rate?

Previous empirical studies in the US have shown that: (1) metros are evolving toward the polycentric (Garreau, 1991; Lee and Gordon, 2007; Matsuo, 2008; Gordon and Richardson, 2012); (2) urban agglomeration economies and diseconomies are not just a result of metro size, but also a result of the urban inner structure (Cervero, 2001; Lee and Gordon, 2007; Matsuo, 2008; Gordon and Richardson, 2012; Garcia-López and Muñiz, 2010); (3) high population density and high employment density contribute to positive economic externalities, while too high a density in terms of either population or employment can result in negative economic externalities (Zheng, 2001; Wheeler, 2003; Lee and Gordon, 2007; Matsuo, 2008); and (4) metros evolving from monocentric to polycentric relieve agglomeration diseconomies (Sasaki and Mun, 1996; Fujita, Thisse, & Zenou, 1997; Lee, 2007).

This research explores US metros' spatial structure evolution patterns and their influence on their employment growth rate from 2000 to 2010. Employment centers are nodes that define a qualitative change in a city's structure (see Figure 1-1). Structural evolution is as a process of worker migration. One or two workers migrating from the main-center to the suburbs, for example, would not cause a qualitative change in the metropolitan spatial structure. However, 10,000 workers migrating from the main-center to the suburbs could substantially change the metropolitan spatial structure. The number of workers might grow, remain the same, or decline, while the spatial distribution of workers might become more dispersed, remain the same, or become more concentrated. Workers' mobility (in terms of both their numbers and their spatial distribution) result in urban spatial structure evolution (or change).

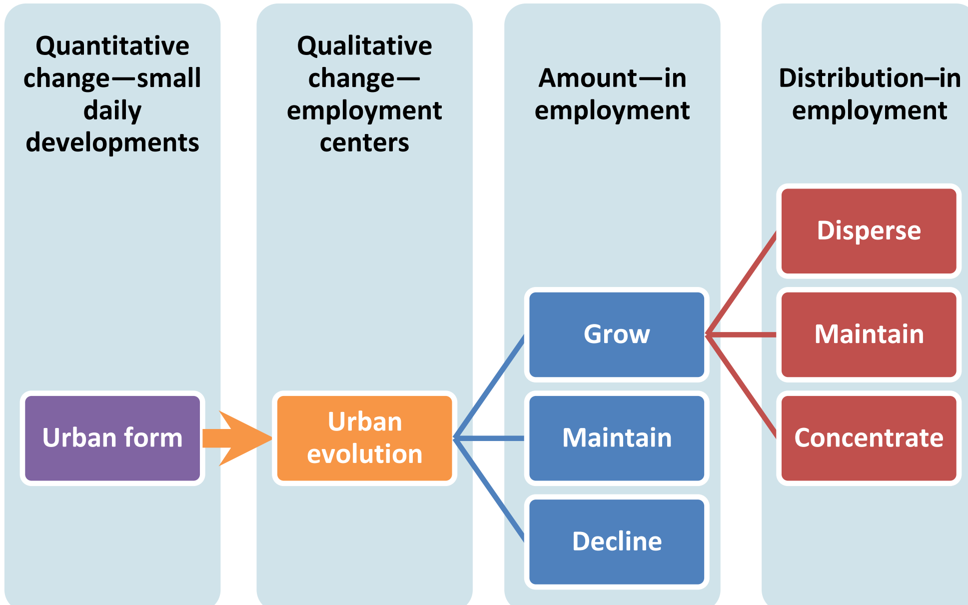


Figure 1-1 Defining structural change by employment

1.2 Research Purpose and Objectives

This study aims to explore US metropolitan spatial structure evolution (from 2000 to 2010) and its influence on regional employment growth. The main research question is: How does the evolution of US metropolitan spatial structure influence regional employment growth rate? This research includes three parts. The first part investigates the evolution paths of US metros' spatial structure from 2000 to 2010. The second part explores the influence of spatial structure evolution on regional employment growth rate. The three research objectives are as follows.

Research Objective 1: find out whether the majority of US metros were polycentric in the first decade of the 21st century. A number of urban studies claim that the US is entering a polycentric (or post-polycentric) era. However, this claim mainly comes from studies done on the largest metros in the US. The studies' sample sizes are small, less than half of the total US metros. Therefore, it is not clear if the US has indeed entered a polycentric (or post-polycentric) era. This study includes 361 metros from all 50 states. Using a much larger sample than those of previous studies, my research results should provide a more complete picture of the US metros' spatial structure at the turn of the century.

Research Objective 2: discover patterns of US metropolitan spatial structure evolution. Cities do not emerge as polycentric in the beginning; polycentric metros evolve from monocentric ones. Studies (e.g., Krugman and Venables, 1995; Garreau, 1991) have suggested that there is a re-concentration period that occurs during a metro's expansion. These studies claim that development occurs at the city's edge. Lang (2003), on the contrary, concludes that office development has always been scattered; cities are edgeless. While each previous study has its merit, none could demonstrate their theory's applicability to all metros, possibly due to the lack of an adequate sample size. This study performs a data-driven quantitative analysis on US metros' evolution patterns from 2000 to 2010 at both the macro and micro levels.

Research Objective 3: assess the influence of spatial structure evolution on regional employment growth rate. Theories supporting the re-concentration process assume that businesses seek agglomeration economies. Most studies use 10,000 workers as the lower limit to define an employment center. However, small size (i.e., less than 10,000 workers) employment clusters may also generate economic externalities. A metro's spatial structure, if based only on employment centers, could fail to capture the metro's real agglomeration economies. In this study, I separate a metro into five submetro sections that represent different sizes and densities of agglomeration units. I conduct a regression analysis to test whether changes (from 2000 to 2010) in employment share of these five agglomeration units have an impact on a metro's employment growth rate.

1.3 Delimitations and Assumptions

This research assumes that a metro would not have undergone more than one type of structural change during the study period. For example, if a metro was monocentric in 2000 and 2010, I assume the metro remained monocentric during the entire period.

I assume people work and live in the same metro. I assess metros' employment growth rates by using U.S. Bureau of Economic Analysis (BEA) data, which include a portion of the employment data collected using respondents' residential addresses. This assumption ensures that the measurement of the employment growth rate fully corresponds to the target metro.

This research does not look into specific changes in individual employment clusters. For example, in a metro with five employment centers, two may disperse while the other three agglomerate. The aggregated effect of these five employment centers at the metro level, however, could be either dispersion or agglomeration. I study the aggregated changes in this dissertation.

This research assumes there is no significant industrial influence on a metro's employment growth rate. The only factor considered able to impact a metro's employment growth rate is its spatial structure. Factors such as capital deepening, increases in human capital, and technological progress may also bring about economic growth (O'Sullivan, 2012). This study assumes there were no significant changes in these factors among US metros during the study period.

1.4 Definitions of Terms

The following is a list of terms used in this study:

- A city is a gathering of economic activities. A city can be a metropolitan area or a municipal city.
- An employment cluster includes both employment centers and non-center clusters. An employment center is an urban area with a high density and a large number of workers. An employment center can be a central business district (CBD), or a suburban business district (SBD). An employment non-center cluster is an urban area with a high density of workers. The difference between an employment center and an employment non-center cluster is that the latter has no requirement for the total number of workers.
- A main-center represents the largest employment center in a metro. The remaining employment centers are sub-centers. A main-center is usually located in the CBD area of a metro.
- An urban spatial structure is the physical framework of a city, and is determined by the distribution of employment clusters (among other factors). Metropolitan spatial structure refers to urban spatial structure in a metropolitan area.

- Macro spatial structure refers to a metro's spatial structure, as defined by its number of employment centers. There are three macro spatial structure types in this study — coreless, monocentric, and polycentric each with zero, one, and more than one employment center, respectively.
- Macro spatial structure evolution refers to a metro's change in macro spatial structure type.
- Micro spatial structure refers to a metro's spatial structure, defined by its employment shares in five submetro sections (i.e., main-center, sub-centers, non-center clusters, non-cluster urban areas, and rural areas). A micro spatial structure type is defined by the ranks of employment shares in a metro.
- Micro spatial structure evolution refers to a metro's change in micro spatial structure type.
- Geographic proximity refers to the closeness of individual objects on the ground. It is synonymous with physical proximity, geographic closeness, and spatial closeness.
- Agglomeration economies are the sum of various positive externalities resulting from the spatial concentration of firms, people, and ideas (e.g., input sharing, labor market pooling, and knowledge spillovers).
- Agglomeration diseconomies are the sum of the various negative externalities that result from agglomeration (e.g., congestion, overcrowding, pollution, and infrastructure shortage).

- Economic growth means an increase in output measured by GDP, employment, or income.

1.5 Significance of the Study

This study provides evidence regarding US metros' spatial structures, complementing previous studies in the literature that focused on individual cities. Understanding metros' evolution trends may help city planners make proactive plans that can relieve agglomeration diseconomies. This study also provides a way for city planners to assess the relationship between the economic performance of a metro and its spatial structure.

This study informs regional economic policies by providing feedback from spatial structures to economic performance. The traditional point of view considers a metro's spatial structure to be static, passively adapting to economic needs. However, the built environment (i.e., metropolitan spatial structure) we create will eventually constrain our activities within (Hillier and Vaughan, 2007). Economic policymakers may make better-informed policies by taking into account feedback effects from the built environment.

This study also helps coordinate the upper and lower levels of government work. In the US, city planning is largely a local activity, at a level that is disconnected from regional economic research. A metro is an economic unit, at a level that is out of the control of local government for urban planning and implementation. This study, however, uses submetro (i.e., census tract) data to reflect local characteristics in metro-level analyses.

CHAPTER II

LITERATURE REVIEW

2.1 US Metropolitan Spatial Structure

2.1.1 Edge or Edgeless

Empirical studies have described the structural evolution of US metros since 1991. Garreau (1991) coined the term "edge city" for the new urban centers emerging from suburbs. He declared "[t]oday, we have moved our means of creating wealth, the essence of urbanism—our jobs—out to where most of us have lived and shopped for two generations. That has led to the rise of Edge City" (p. 4). Older centers are no longer the only urban center that everything else has to surround. Garreau's (1991) Edge City has the following characteristics:

- Has five million square feet or more of leasable office space – the work place of the Information Age.
- Has 600,000 square feet or more of leasable retail space.
- Has more jobs than bedrooms.
- Is perceived by the population as one place.
- Was nothing like a "city" as recently as thirty years ago (p.6-7).

Based the above definition, Edge Cities should be a recent phenomenon characterized both qualitatively (e.g., residents' perception of the Edge City as one place) and quantitatively (e.g., at least five million square feet of leasable office space).

A decade later, Lang (2003) claimed that US metros were edgeless, in terms of office area development. “The term ‘edgeless city’ captures the fact that most suburban office areas lack a physical edge” (p.2). In his study, “edge cities (or office clusters with more than 5 million square feet of office space, with or without major retail space) currently account for only one-third of all non-downtown office space, while edgeless cities make up the remaining two-thirds.” To explain this inconsistency with Garreau’s (1991) study, Lang argued “edge cities did experience a burst of growth in the mid-to late 1980s, at the time that Garreau was observing them. Edge city growth has since slowed, while edgeless cities seem to have grown at a steadier pace” (p.12)

Furthermore, Borgart (2006) observed a network-like metropolitan form, with “trading places” as the nodes. He argues:

> Even the polycentric city model is insufficient to capture the richness of the interconnections in the modern metropolitan area. When only about half of all employment is concentrated into employment centers, the diffusion of production, consumption, and trade throughout the metropolitan areas has gone to a new level. Rather than focus narrowly on bilateral trade between bedroom suburbs and downtowns, we are now forced to consider a complicated web of trade in goods and services among a wide range of economies within the metropolitan area. I call these local economies *trading places* to capture both their diversity and their interaction with each other (p.11).

In summary, Garreau (1991) observed the birth of new urban centers in suburbs. Lang (2003) found that office sprawl was everywhere throughout US metros and was never gone, and the new urban centers in suburbs are not agglomerating to distinctive centers. Lang (2003) blurred the polycentric image of US metros that Garreau (1991) observed. Furthermore, Bogart (2006) argued polycentricity is too distinctive of a form for US metros. He referred to employment clusters as trading places to emphasize there is more than bilateral trade between the central city and suburbs. However, all these are descriptive case studies. They vary in study areas, study periods, and measurement methods for spatial structure. This study will paint a more complete picture of US metros' spatial structures in 2000 and 2010.

2.1.2 Measurement of Metropolitan Spatial Structure

2.1.2.1 Measurement of Spatial Structure by Distance

Metropolitan spatial structure can be measured by share (or distance based on the locations) of employment or population. A typical metro's land area is occupied by a series of firms, residences, and public spaces. The employment distribution indicates the locations of firms, while the population distribution indicates the locations of residences. The rest of the land area in a metro is public space.

Distances among the locations of employment, population, and public spaces can lead to multiple distinctive dimensions of a metropolitan spatial structure--density, continuity, concentration, centrality, nuclearity, mixed uses, and proximity (Cutsinger, et al., 2005). These dimensions can be measured by the locations of population and employment, or a combination of both.

Density. El Nasser and Overberg (2001) created a USA TODAY Sprawl Index, which refers to the percentage of a metro area's population that lives in "urbanized areas." Fulton et al. (2001) advanced the measurement by applying it to actual urbanized land, claiming that the Census Bureau's definition of "urbanized area" does not measure actual land use. Lopez and Hynes (2003) improved the study by employing data at a finer level – the Census tract, which helps detect the relative concentration of population within a metro.

Continuity. The dimension of continuity refers to "the degree to which developable land has been built upon at urban densities in an unbroken fashion" (Galster et al., 2001, p.688). To incorporate areas outside of urban area (UA) and land uses other than residential, continuity is defined as "[t]he degree to which developable land has been developed (for any urban uses) in an unbroken fashion throughout the metropolitan area" (Cutsinger et al., 2005, p.238; Wolman et al., 2005; Cutsinger and Galster, 2006). This dimension is mainly used to emphasize urban problems resulting from a "leap-frogging" development pattern. Leap-frogging refers to the type of urban development extending from the built urban area in a discontinuous way.

Concentration. The dimension of concentration measures "the degree to which development is located disproportionately in relatively few square miles of the total UA rather than spread evenly throughout." (Galster et, al., 2001). However, concentration is commonly used in different study contexts. It generally refers to a gathering of population or employment in a metro area. Jacobs (1961) argues that "[t]he district must have a sufficient dense concentration of people, for whatever purpose they may be there"(p.200). Concentration is one of the two most widely used dimensions regarding urban spatial structure. The other one is centrality.

Centrality. The dimension of centrality measures “the degree to which residential or nonresidential development (or both) is located close to the central business district (CBD) of an urban area” (Galster et, al., 2001). This dimension captures the phenomenon known as “suburbanization.”

Nuclearity. The dimension of nuclearity measures “the extent to which an urban area is characterized by a mononuclear (as opposed to a polynuclear) pattern of development.” (Galster et al., 2001) That is to say if a metro has more than one locus, the metro’s nuclearity will decrease.

Mixed use. The dimension of mixed use measures “the degree to which two different land uses commonly exist within the same small area and this is common across the UA” (Galster et al., 2001). Ewing (1997) and Burchell et al. (1998) believe mixed use can help promote biking and walking, and discourage auto dependency. Jacobs (1961) argues “the district, and indeed as many of its internal parts as possible, must serve more than one primary function; preferably more than two. These must insure the presence of people who go outdoors on different schedules and are in the place for different purposes, but who are able to use many facilities in common” (p.152).

Proximity. The dimension of proximity measures “the degree to which different land uses are close to each other across a UA” (Galster et al., 2001). Weitz and Crawford (2012) assessed job accessibility by calculating the distance between jobs and populated places using a gravity model, and concluded “from 2001 to 2006 in the vast majority of MSAs, jobs became more inaccessible relative to census-defined populated places” (p.67).

Connectivity. Spatial structure can be measured by connectivity. In practice, travel cost, rather than Euclidean distance, matters in transport. Connectivity is more simplified than accessibility since the latter may require an assessment of the attributes of the origin and destination. Ewing equates sprawl to "poor accessibility" and asserts that "[s]treet networks can be dense or sparse, interconnected or disconnected, straight or curved. Blocks carved out by streets can be short and small, or long and large. Sparse, discontinuous, curvilinear networks creating long, large blocks have come to be associated with the concept of sprawl while their antithesis is associated with compact development patterns" (Ewing, 1997; Ewing et al., 2002, p.24).

Table 2-1 presents urban spatial structure measurement by distance. It reveals several important points. First, it suggests that urban sprawl is a multi-dimensional, multi-scale and multi-scope phenomenon. Multi-dimensional refers to its many sprawling patterns; multi-scale means it can be assessed at different geographic scales, and multi-scope denotes that it can be identified through population, residential units, and employment. Second, the finer the data summary level, the fewer the number of observations; that is, finer levels of data are less available. Ewing et al. (2002) have also admitted, "[t]he second big decision in developing a sprawl index is exactly which patterns should qualify as sprawl. In this study, the decision is largely dictated by data availability. Because I am attempting to measure sprawl for metropolitan areas across the United States, data have to be available from national sources." (p.3) Third, the measurement area starts to embrace edge cities with a polycentric view (Yang et al., 2012; Weitz and Crawford, 2012).

Table 2-1 Urban spatial structure measurement by distance

Author	Measurement subject	Dimension	Number of observations	Data summary level
El Nasser and Paul Overberg(2001)	Population	Density	271	Urbanized areas by Census
Fulton, Pendall, Nguyen and Harrison(2001)	Population	Density	281	Urbanized areas by Census
Lopez and Hynes (2003)	Population	Density, concentration	330	U.S. Census tract
Galster, Hanson, Ratcliffe, Wolman, Coleman and Freihage (2001)	Residential unit	Density; concentration; clustering; centrality; nuclearity; proximity	13	U.S. Census block
Ewing, Pendall and Chen (2002)	Residential unit; population; employment	Density; mixed uses; centrality; accessibility	83	TAZ; block groups; tracts; neighborhood
Song and Knaap (2004)	Residential unit; employment	Street network connectivity; density; land use mix; accessibility; and pedestrian walkability	3	TAZ
Weitz and Crawford (2012)	Employment	Distance	358	Five-digit county business patterns; populated places
Burchfield, Overman, Puga and Turner (2006)	Residential area	Coverage	275	Square kilometer
Cutsinger and Galster (2006)	Residential unit; employment	Density, continuity, concentration, centrality, proximity, nuclearity, and mixed use	50	Square mile

2.1.2.2 Measurement of Spatial Structure by Employment Share

Economists assess employment decentralization using employment shares near the CBD. Glaeser, Kahn and Chu (2001) calculated employment shares within a three-mile ring of the Central Business District, within a ten-mile ring, and beyond the ten-mile ring to overall metro employment (within 35 miles). They claimed that the three-mile ring would capture whether the metropolitan area had a well-defined employment center, and the ten-mile one would capture the extent to which the metropolitan area is characterized by sprawl. Similar approaches can be found in Stoll (2006), Kneebone (2009), Lee and Gordon (2007) and Burchfield et al. (2006).

One drawback to this approach is that there is an interesting lack of dialogue between economists and geographers; see Table 2-2. A research method combining the merits of the two would benefit both disciplines.

Table 2-2 Approaches on spatial structure measurement

Researchers	Metropolitan spatial structure dimensions	Metropolitan spatial viewpoint
Urban economists	Size and density (by employment share)	Polycentric
Urban geographers	Density, continuity, concentration, clustering, centrality, nuclearity, mixed uses, and proximity (by distance)	Monocentric

2.1.3 Delimitation of Urban and Rural Lands

Urban analysis typically requires the separation of a metro's urban and rural areas. Lee (2007) claimed, "[a]ll these (particularly centralization) indices are sensitive to the presence of large, unpopulated census tracts in outlying areas due to the well-known mismatch of administrative boundaries and functional areas." (p. 485) Delimiting urban and rural lands is necessary, but there is no perfect way to accomplish this separation.

There are absolute and relative threshold methods used to delimit urban and rural lands. The absolute threshold method generally applies a universal cutoff value for all (metro) areas. For example, before identifying employment centers for Los Angeles, Giuliano et al. (2007) applied the Census definition to exclude rural tracts. The Census defined an urbanized area as having more than 1,000 persons per square mile. Lopez and Hynes (2003) argued that this definition inappropriately excludes large areas of developed land. The Census definition also changes as population increases (Kline, 2000). Instead, Lopez and Hynes (2003) and Fulton et al. (2001) defined urban areas as places with more than 200 persons per square mile. Alternatively, the relative threshold method sets a threshold by considering the conditions of a specific metro area. For example, Lee (2007) and Wheaton (2004) exclude the least populated census tracts to keep 95 percent and 98 percent, respectively, of a metro's total population.

For this study, I apply the relative threshold method used by Lee (2007) and Wheaton (2004) to employment data (Lee and Wheaton used population data). I choose the relative method over using a universal cutoff (Census, 2000; Lopez and Hynes, 2003; Fulton et al., 2001) because using a universal cutoff for all metros could shift the statistical research results. For example, Arizona metros might have to exclude more workers than New York metros; similarly, a rural tract in New Jersey might have a higher worker density than one in urban Alaska. On the other hand, employment is a better agent than population for capturing urban activity because population is measured based on primary residence. For example, some CBD areas have zero residential development, but these areas are not rural.

2.1.4 Metropolitan Employment Centers

Von Thünen's (1966) theory on agricultural land use laid the groundwork for later monocentric city modeling. It describes land-rent making up for transport cost. Alonso (1964) used the land rent-transport cost rationale, but put the model in a more realistic urban environment. He assumed a CBD is where all jobs are located. Residents' lives surround the CBD, but the distance (transport cost) is determined by income and land rent. Theoretically, land rent would go down as distance to the CBD increases. During the 1980s, scholars inferred that the monocentric model no longer held for US metros because they found housing price gradients appearing as peaks far away from the CBD (Bender and Hwang, 1985; McDonald, 1987). Thus, they searched for polycentric explanation.

Subcenters are the deviation from predicted population density or housing price found by regressing on distance from CBD (Odland, 1978; Bender and Hwang, 1985). To operationalize indicators for employment centers, McDonald (1987) notes, "Five definitions of employment subcenter at first appear to be reasonable: a secondary peak in gross employment density, net employment density, employment-population ratio, gross population density, and net population density" (p.243). Based on an empirical study on Chicago, he concluded gross employment density and employment-population ratio are the best measures.

Methods identifying employment centers involve either absolute or relative density threshold criteria (Lee, 2007; Giuliano et al., 2005). There are three types of methods; see Figure 2-1. The type I method was introduced by Giuliano and her colleagues, using an absolute density and a total employment threshold. The type II method was introduced by McMillen and McDonald (1997). This method typically applies a regression model (e.g., locally weighted regression) on distance from the CBD to identify secondary density peaks and then use a geographic window to ensure the secondary peak have higher density than its surrounding area, The type III method uses a unique density threshold for each metro based on the metro's employment distribution. Lee (2007) set thresholds at 90-percentile employment density for six metros. Pan and Ma (2006) applied an 87.7-percentile (corresponding to 10 workers per acre) density as threshold for Houston metropolitan area. Agarwal et al. (2012) summarized empirical work in two Tables: 2-3 and 2-4.

Table 2-3 Select studies of employment centers in Los Angeles metropolitan area

Author	Employment center definition used	Study period	# of centers
Giuliano and Small (1991)	Employment density ≥ 10 jobs/acre; total employment ≥10,000	1980	35
Forestall and Greene (1997)	Jobs/workers ≥ 1; and at least one tract with jobs/workers ≥ 1.25	1990	120
Giuliano et al. (2007)	Employment density ≥ 10 jobs/acre; and total employment ≥ 10,000	1990	46
		2000	48
Giuliano et al. (2007)	Employment density ≥ 20 jobs/acre; and total employment ≥ 20,000	1990	13
		2000	15
Redfearn (2009)	Locally weighted regression and statistical algorithms	2000	41
Lee (2007)	Locally weighted regression to identify potential centers; minimum total employment criterion > 10,000 to select final centers	2000	44

(source: Agarwal, Ajay, Genevieve Giuliano, and Christian L. Redfearn. "Strangers in our midst: the usefulness of exploring polycentricity." The Annals of Regional Science 48.2 (2012): 433-450.)

Table 2-4 Select employment center studies

Author	Study period	Metropolitan area	No. of centers
McMillen and McDonald (1997)	1980	Suburban Chicago MSA (excludes city of Chicago)	15
Anderson and Bogart (2001)	1990	Cleveland	9
		Indianapolis	11
		Portland	11
		St. Louis	10
McMillen and Smith (2003)	1990	62 MSAs	Various
Giuliano et al. (2007)	1980	Los Angeles CMSA	36
	1990		46
	2000		48
Lee (2007)	1990	New York	34
		Los Angeles	44
		Boston	10
		San Francisco	22
		Portland	3
		Philadelphia	14
	2000	New York	35
		Los Angeles	42
		Boston	8
		San Francisco	18
		Portland	3
		Philadelphia	11

(source: Agarwal, Ajay, Genevieve Giuliano, and Christian L. Redfearn. "Strangers in our midst: the usefulness of exploring polycentricity." The Annals of Regional Science 48.2 (2012): 433-450.)

Based on the purpose of this study, I primarily use an improved Type III method to identify employment centers; this method should be capable of capturing each metro's internal structural characteristics, as well as be convenient to operate for a large sample of metros and easy to apply in terms of structure management. On the contrary, Type I and II methods have the following drawbacks:

- A Type I method is subject to bias; that is, it may only be able to capture the characteristics of high-density metros. This method is not applicable for large sample studies.

- A Type II method results in inconsistent density thresholds within a metro, which complicates the calculations for and management of metropolitan spatial structures. Second, a Type II method requires a pre-defined CBD location. Third, a Type II method is arbitrary in choosing "significance level, geographic window size, and weight of distance" (Matsuo, 2008, p. 27).

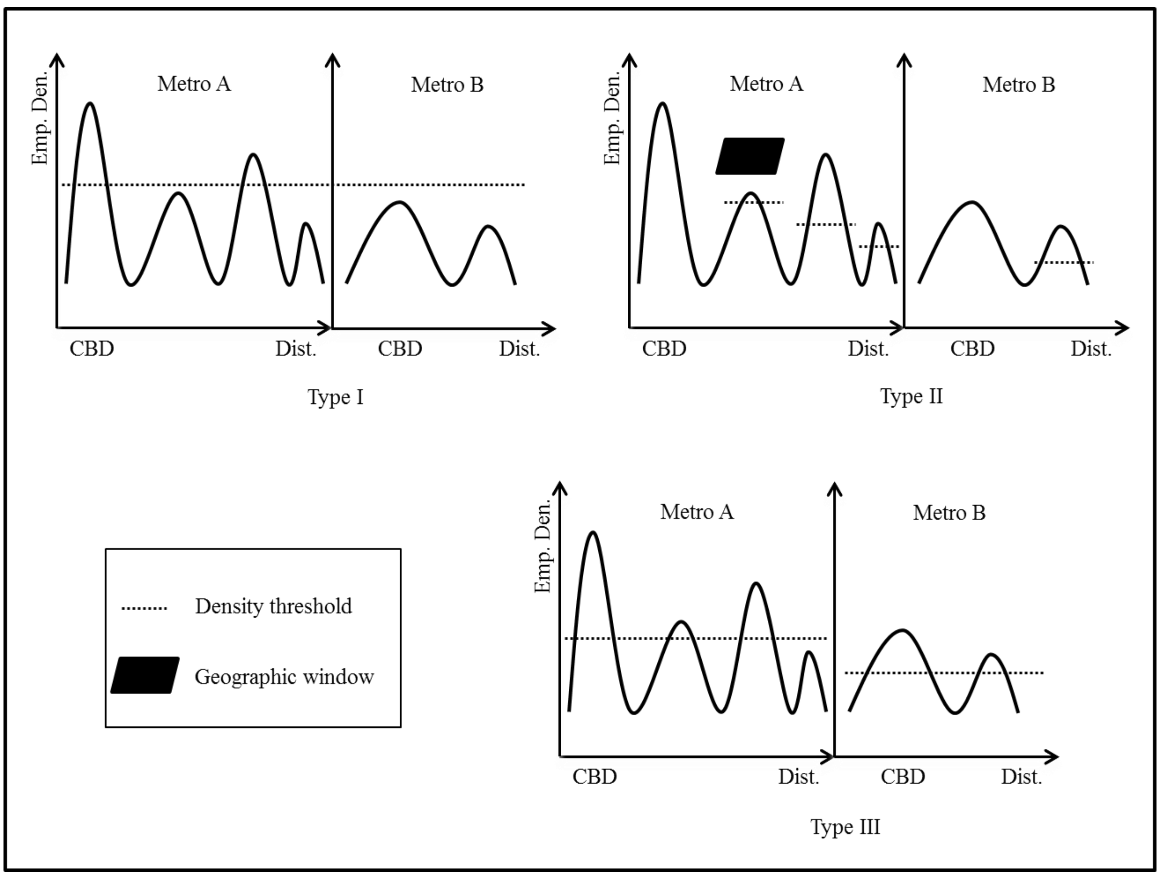


Figure 2-1 Methods for identifying employment centers

2.2 Metros as Agglomeration Economies

2.2.1 Localization and Urbanization Economies

Cities exist to take advantage of agglomeration economies. Agglomeration literally means to gather within a small land area. In urban economics, the gathering of people and firms is said to generate benefits or externalities, which are called "agglomeration economies." The extensive yet inconsistent empirical studies on agglomeration extend to at least three dimensions: industrial, geographic, and temporal; and "in each case, the literature suggests that agglomeration economies attenuate with distance" (Rosenthal and Strange, 2004, p. 2120). Put another way, the effects of agglomeration differ with closeness of industrial subdivisions (industrial scope), fade or accumulate with time (temporal scope), and attenuate with distance (geographic scope).

Agglomeration economies usually present as an amalgam of localization economies and urbanization economies. Localization economies are the type of agglomeration externalities generated within industry through input sharing, labor-market pooling, and knowledge spillovers (Marshall, 2004). Unlike most empirical studies conducted at the metropolitan level, Marshall actually proposed the idea of agglomeration at the neighborhood level. In contrast with Marshall's idea of localization, urbanization economies are generally understood as inter-industry agglomeration economies. This point was brought up by Jacobs (1969). She emphasized the importance of diversity in innovation and thus economic growth to metros. Glaeser et al. (1992), using an urban growth model, tested Romer (1986), Porter (1998) and Jacobs' (1961) economic growth theories. The former two believe "the engine of growth" – knowledge spillover--comes from intra-industry specialization with or without competition. Jacobs' theory believes growth comes from inter-industry diversity with competition. They found the growth of large industries in US metros between 1956 and 1987 support Jacobs' theory, although they also believe that specialization (Romer and Porter's theory) might be significant for young industries.

Recently, studies have also attempted to measure the impact distance of urbanization economies. Based on Rosenthal and Strange's (2003) model using new births as evidence of agglomeration economies' presence, Rosenthal and Strange (2008) this time found evidence of both localization economies (an establishment's own 2- digit industry) and urbanization economies (overall activity nearby) within 5 miles. Partridge, Olfert and Alasia (2007) assessed the effect of agglomeration economies in the few major Canadian metropolitan areas on population growth in and near these metros. They found that positive marginal effects from proximity to major centers extend out about 830km for urban centers, and 800km for rural, small towns and Census consolidated subdivisions, which implies that the positive forces of urban agglomeration extend far beyond their major center's boundaries --much further than the localized effects.

2.2.2 Urban Spatial Structure and Economic Growth

Urban spatial structure relates to economic growth because of agglomeration economies. The measurement of urban spatial structure may use employment or population. Note that accessibility between employment and population is also measurement of urban spatial structure. On the other hand, the measurement of economic growth may be labor productivity, population, employment, and labor accessibility (assuming higher accessibility resulting in larger agglomeration economies).

Cervero (2001) explored the relationship between labor productivity and urban spatial structure in metro San Francisco. He found worker productivity was positively associated with employment densities and urban primacy at the metropolitan level. The positive relationship was also reinforced at the intrametropolitan level – “labour productivity appears to increase with size of labour-marketshed and high accessibility between residences and firms.” (p. 1651) However, Lee and Gordon (2007) criticized Cervero’s (2001) work for not controlling capital input while doing labor productivity analysis.

Lee and Gordon (2007) tested the relationship between urban spatial structure and economic growth by adding a spatial variable to Glaeser et al.’s (2003) model. They found that “[a] metropolitan area with more clustered spatial form grows faster, perhaps enjoying agglomeration economies when it is small; whereas more dispersion leads to higher growth rate as it grows large.” (p.13) They measure dispersion as “Percent dispersed location share of total employment,” and polycentricity as “Subcenters’ share of center employment: [subcenter’ emp. / (subcenters’ emp. + CBD emp.)] * 100.” Neither dispersion nor polycentricity is significant in their model. The reason might be that employment centers are not the only evidence for the presence of agglomeration economies.

Meijers and Burger (2010) analyzed the effect of spatial structure on labor productivity, controlling for capital-labor ratio, land-labor ratio, and human capital. They use population to measure dispersion and polycentricity in Combined Statistical Areas in 20006. Dispersion measures the degree to which population locates in nonurban areas. Polycentricity measures the degree to which population concentrated evenly in different urban centers. They found polycentricity has a positive effect on labor productivity while dispersion does not. On the contrary, Matsuo (2008) analyzed four US metros and found employment centers in polycentric form are less accessible because they suffer from both a modest residential density and slow traffic.

In summary, these studies do not conflict but complement one another. These findings support that (1) high density contributes to agglomeration economies, (2) dispersion does no harm to agglomeration economies, and (3) polycentricity may benefit agglomeration economies if urban centers are not too highly concentrated. However, these studies have different results because authors use different agents (e.g., employment, population) measuring different agglomeration units (e.g., employment center, urban center, urban primacy, metropolitan area).

CHAPTER III

CONCEPTUAL FRAMEWORK AND RESEARCH HYPOTHESES

This chapter has three sections, each illustrating a conceptual model:

- Conceptual model 1—classify spatial structures at both the macro and micro levels;
- Conceptual model 2—determine spatial structure evolution at both the macro and micro levels;
- Conceptual model 3—model spatial structure evolution and employment growth at both the macro and micro levels.

3.1 Classifying Spatial Structures

3.1.1 Conceptual Model 1

The purpose of model 1 is to classify US metros' macro and micro spatial structure types (see Figure 3-1). At the macro level, I group metros into three categories, according to their number of employment centers in 2000 and 2010. The macro spatial structure types are monocentric, polycentric, or coreless. Monocentric metros have only one employment center. Polycentric metros have more than one employment center. Coreless metros have no employment center.

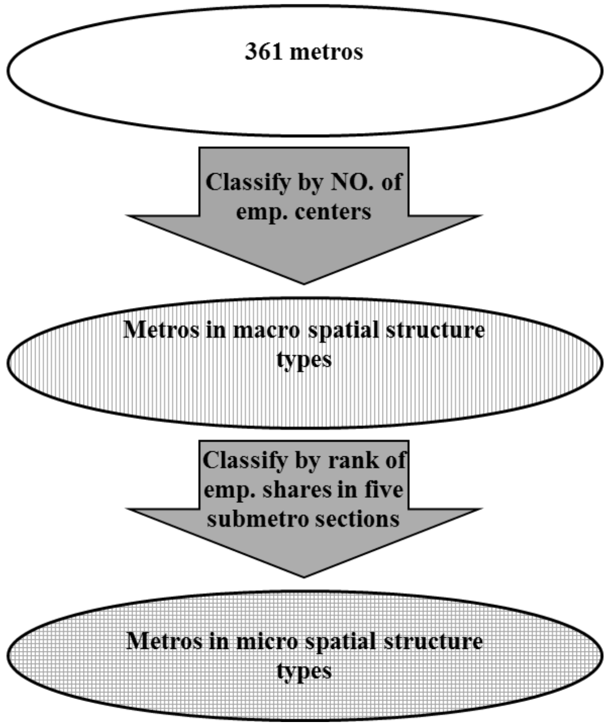


Figure 3-1 Conceptual model 1—classification of US metropolitan spatial structures

A metro's micro spatial structure type is defined by its rank of employment shares in five submetro sections (i.e., the main-center, sub-centers, non-center clusters, non-cluster urban areas, and rural areas); see Figure 3-2. The sum of the employment in the five submetro sections (X_1 to X_5) equals the metro's total employment (Y). Structural indicators describe the ratio of the employment share in each submetro section to the total employment of the metro. A metro's total employment Y is:

$$Y = X_1 + X_2 + X_3 + X_4 + X_5 \qquad \text{(Equation 3-1)}$$

The five structural indicators are:

$Z_i = \frac{X_i}{Y}, i = 1,,5$ (Equation 3-2)

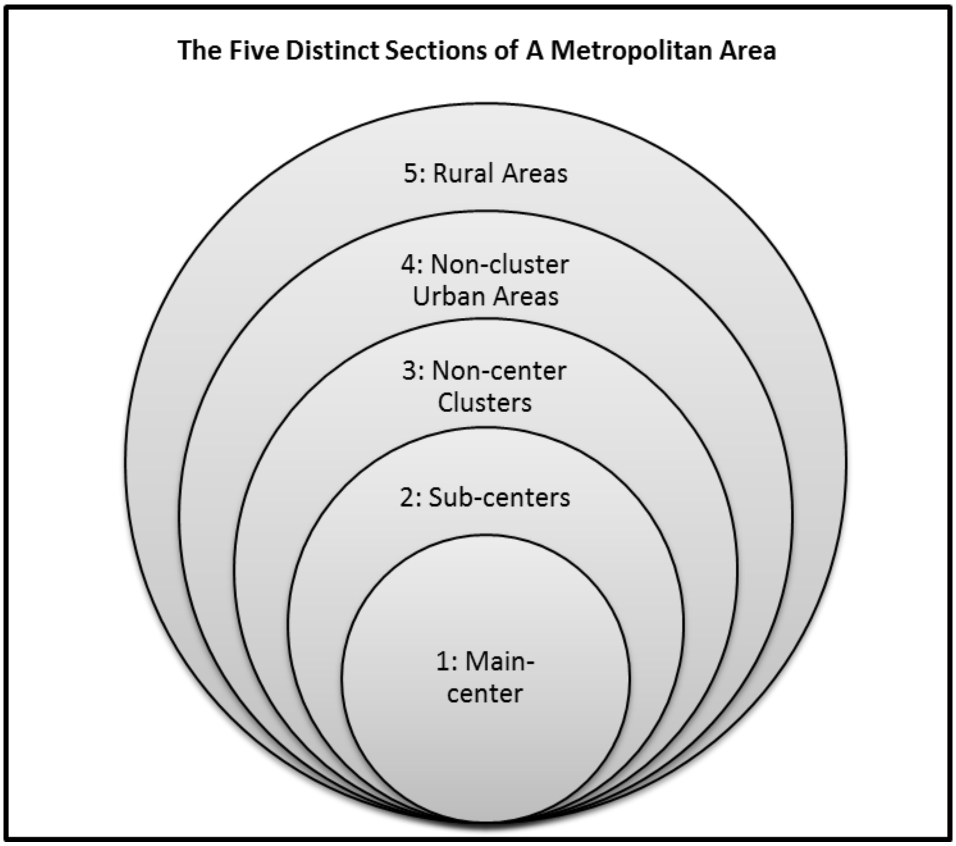


Figure 3-2 A metropolitan area's five submetro sections

The evolution indicators are the difference in structural indicators between 2000 and 2010. The structural indicators in 2010 are indicated by $\frac{X_i''}{Y''}$, and $\frac{X_i'}{Y'}$ are the structural indicators in 2000.

$$Z_{i_{dif}} = \frac{X_i''}{Y''} - \frac{X_i'}{Y'} \qquad \text{(Equation 3-3)}$$

Where,

i –section code, i = 1(main-center), i = 2(sub-centers), i = 3(non-center clusters), i = 4(non-cluster urban areas), i = 5(rural areas);

X_i'—2000 section i employment;

X_i''—2010 section i employment;

Y'—2000 metropolitan total employment;

Y''—2010 metropolitan total employment;

Z_i—structural indicator at section i;

$Z_{i_{dif}}$—evolution indicator at section i.

3.1.2 Hypothesis 1

There are two main claims regarding US metros' spatial structures since the 1990s. The first is that a number of large metros are polycentric. The second is that most employment is located outside of the centers. Giuliano et al. (2008) concluded that "[t]he share of employment outside [the] centers is in the range of two-thirds to three-fourths," after reviewing case studies in the literature (p. 29). This study will test (1) whether polycentricity prevailed in all US metros, and (2) whether employment outside of the centers dominated US metros. Hypothesis 1 includes two sub-hypotheses; hypothesis a and hypothesis b test US spatial structure at the macro and micro levels, respectively.

Hypotheses 1:

a. The majority of US metros were polycentric in 2010.

b. The share of employment in outside centers accounted for two-thirds to three-fourths of the metros' total employment.

3.2 Discovering Spatial Structure Evolution Paths

3.2.1 Conceptual Model 2

The purpose of model 2 is to discover US metros' spatial structure evolution paths at both the macro and micro levels. A metro's macro spatial structure evolution is defined by the change in the metro's macro spatial structure type (see Figure 3-3). I use "n" to denote the number of employment centers. The number of each arrow denotes the type of evolution path:

Type 1--coreless metros remain coreless (coreless→coreless);

Type 2--coreless metros evolve into monocentric (coreless→monocentric);

Type 3—coreless metros evolve into polycentric (coreless→polycentric);

Type 4--monocentric metros evolve into coreless (monocentric→coreless);

Type 5--monocentric metros remain monocentric (monocentric→monocentric);

Type 6--monocentric metros evolve into polycentric (monocentric→polycentric);

Type 7--polycentric metros evolve into coreless (polycentric→coreless);

Type 8--polycentric metros evolve into monocentric (polycentric→monocentric);

Type 9--polycentric metros remain polycentric (polycentric→polycentric).

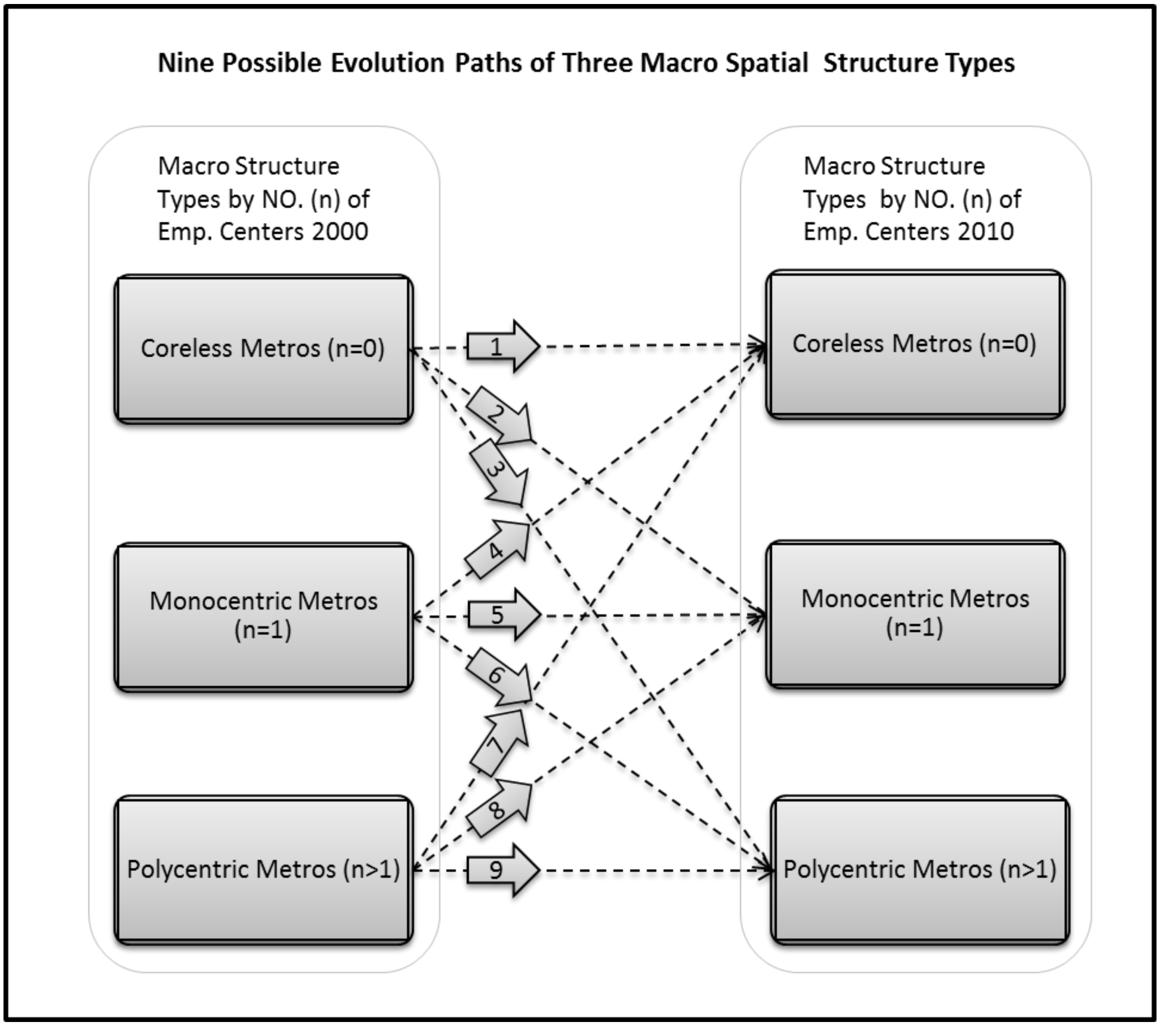


Figure 3-3 The paths of macro spatial structure evolution

A metro's micro spatial structure evolution is defined by the change in the metro's micro spatial structure type. Conceptual model 2b further divides the three macro spatial structure types into micro-level clusters based on the ranking of each metro's five structural indicators (see Figure 3-4).

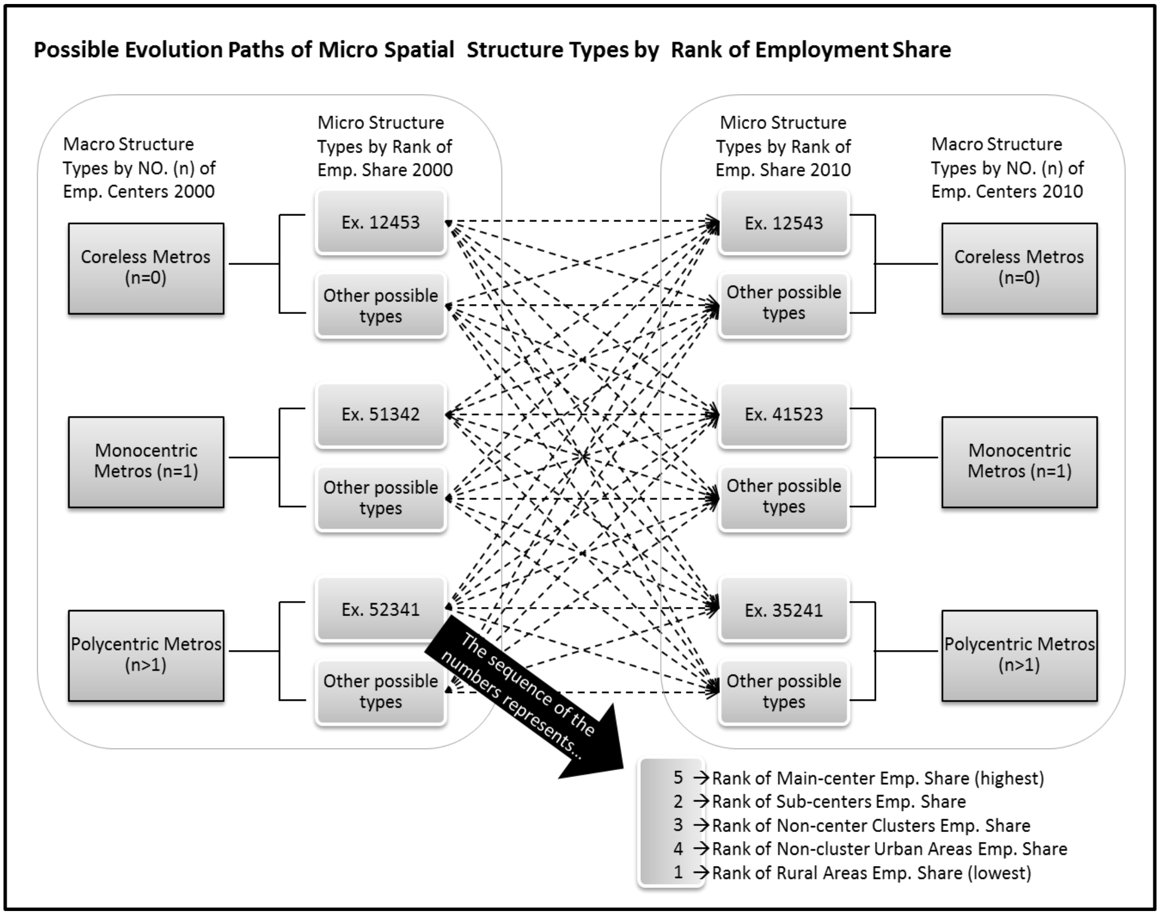


Figure 3-4 The paths of micro spatial structure evolution

Each micro spatial structure in 2000 could evolve into a different micro spatial structure in 2010 (inside or outside of its original macro spatial structure type). Therefore, conceptual model 2b could reveal associations between micro spatial structures and macro spatial structure evolution.

3.2.2 Hypothesis 2

Hypothesis 2 tests US metros’ evolution paths at both the macro and micro levels. At the macro level, it tests whether the majority of US metros evolved from monocentric to polycentric from 2000 to 2010. At the micro level, it tests: (1) whether employment decentralization continued on from the 1980s trend, and (2) whether employment centers remain stable as the literature has suggested (Giuliano et al., 2008).

Hypothesis 2:

a. The majority of monocentric metros evolved to be polycentric from 2000 to 2010.

b. The majority of metros had their main-center employment share ranking decrease from 2000 to 2010.

c. The majority of metros had their number of employment centers remain the same from 2000 to 2010.

3.3 Modeling Spatial Structure Evolution and Employment Growth

3.3.1 Conceptual Model 3

The purpose of model 3 is to explore the influence of spatial structure evolution on regional employment growth rate. At the macro level, conceptual model 3a compares the employment growth rates of metros on different evolution paths (see Figure 3-5). For example, conceptual model 3a reveals whether the group of monocentric metros evolving to be polycentric had a higher regional employment growth rate than the group of monocentric metros that remained monocentric.

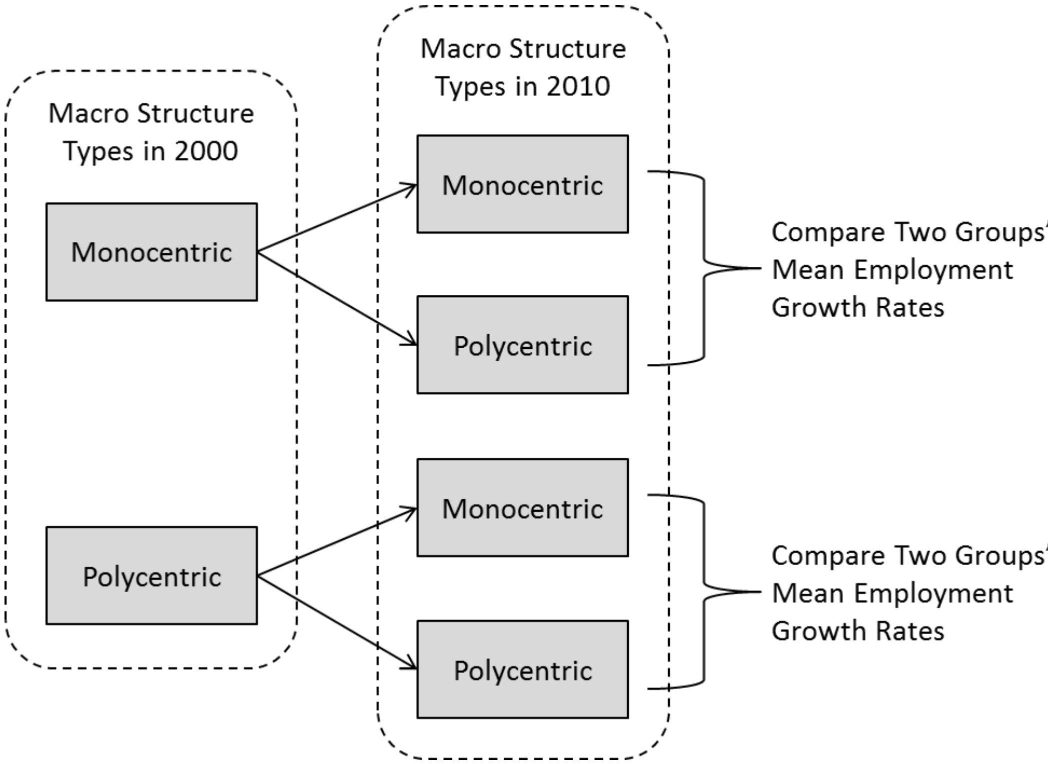


Figure 3-5 Macro spatial structure evolution and employment growth

At the micro level, conceptual model 3b explores how micro-level structural change influences regional employment growth rate. Evolution indicators reflect micro-level structural changes in a metro. Table 3-1 shows the definitions of the independent and dependent variables.

Table 3-1 Micro spatial structure evolution and employment growth

<table>
<tr><td>Dependent Variable</td><td colspan="2">Regional employment growth rate from 2000 to 2010</td></tr>
<tr><td rowspan="11">Independent Variables</td><td rowspan="5">Five evolution indicators (employment share changes from 2000 to 2010)</td><td>Main-center</td></tr>
<tr><td>Sub-centers</td></tr>
<tr><td>Non-center clusters</td></tr>
<tr><td>Non-cluster urban areas</td></tr>
<tr><td>Rural areas</td></tr>
<tr><td rowspan="5">Five initial structural indicators (year 2000 employment shares)</td><td>Main-center</td></tr>
<tr><td>Sub-centers</td></tr>
<tr><td>Non-center clusters</td></tr>
<tr><td>Non-cluster urban areas</td></tr>
<tr><td>Rural areas</td></tr>
<tr><td>Initial metro size</td><td>Year 2000 metro total employment</td></tr>
</table>

3.3.2 Hypothesis 3

At the macro level, the difference between a monocentric and a polycentric metro is the number of employment centers. An employment center represents a large, high density employment concentration. Given the highly dispersed US metros (Huang, 2007), employment concentration will more likely result in agglomeration economies than agglomeration diseconomies. Therefore, I predict metros evolving to metro types with more employment centers will have higher employment growth rates.

At the micro level, metros are further distinguished from one another by their employment shares in the five submetro sections. Different submetro sections represent different types of employment agglomeration. For example, a sub-center is larger in size than a non-center cluster; non-cluster urban areas have lower employment densities than the main-center, sub-centers, and non-center clusters. I predict that submetro sections of a larger size and with a higher density will contribute more to employment growth rate.

Hypothesis 3 consists of four sub-hypotheses (i.e., 3a, 3b, 3c, and 3d). Hypotheses 3a and 3b test the influence of macro spatial structure evolution on employment growth rate. Hypotheses 3c and 3d test the influence of micro spatial structure evolution on employment growth rate.

Hypothesis 3: More employment concentration results in higher employment growth rate.

a. Monocentric metros that remain monocentric have a lower employment growth rate than monocentric metros evolving to be polycentric.
b. Polycentric metros remaining polycentric have a higher employment growth rate than polycentric metros evolving to be monocentric.
c. Employment sub-centers will contribute more to employment growth rate than employment non-center clusters.
d. Employment non-center clusters will contribute more to employment growth rate than non-cluster urban areas.

CHAPTER IV

METHOD

4.1 Data Sources

4.1.1 The U.S. Census Topologically Integrated Geographic Encoding and Referencing (TIGER)

TIGER files use points, lines, and polygons to represent geographic entities such as locations, roads, and areas, respectively. I import a subset of the U.S. Census TIGER shape files, specifically the Census Cartographic Boundary Files, into ArcGIS 10 (a spatial data processing software) to define metro boundaries--the Metro Core Based Statistical Areas (MCBSA). As discussed later, I use census tract polygons with employment data to construct different types of employment clusters within these MCBSAs.

MCBSA polygons define the boundaries of study units. They are the metro areas (instead of micro areas) in the Core Based Statistical Area (CBSA) system. The U.S. Office of Management and Budget (OMB) released the definition for a CBSA in 2003 as follows:

> The term "Core Based Statistical Area" (CBSA) is a collective term for both metro and micro areas. A metro area contains a core urban area of 50,000 or more population, and a micro area contains an urban core of at least 10,000 (but less than 50,000) population. Each metro or micro area consists of one or more counties and includes the counties containing the core urban area, as well as any

adjacent counties that have a high degree of social and economic integration (as measured by commuting to work) with the urban core." (Available at: http://www.census.gov/population/metro/)

I choose MCBSAs as study units for three reasons. First, metros capture true urban growth because they incorporate areas with high economic connections to the urban centers. A portion of people moved to suburbs still work in the central city (Glaeser et al., 1995). Second, MCBSAs result from the most recent OMB definition of metros. US Census TIGER data files based on the old US OMB definition (i.e., MSA - metropolitan statistical area) are difficult to analyze because the files include combined MSAs (i.e., CMSA - consolidated metropolitan statistical area and PMSAs - primary metropolitan statistical areas) into the general data set. For example, some TIGER shape files contain both MSAs and PMSAs. If I extract "MSA" from TIGER shape files, the result will exclude some MSAs (e.g., Miami metropolitan area) because they (e.g., Miami metropolitan area) are under the attribute of "PMSA" which might cover several MSAs. Third, many other data sources (e.g., the employment data from the U.S. Bureau of Economic Analysis) have been updated to be consistent with CBSAs, instead of MSAs.

In the US (and Puerto Rico), there are 370 MCBSAs in the Census 2000 TIGER shape file. However, the eight Puerto Rico metros are excluded because no employment data is available. Within the 362 MCBSAs, Bristol, VA became part of Kingsport-Bristol-Bristol, TN-VA. Therefore, there are 361 MCBSAs under study (see Appendix 1 for detail).

Within MCBSA polygons are census tract polygons. Each census tract polygon has an ID, based on which external table data can be joined to the polygon. If multiple polygons merge, only one ID will be kept for the resulting polygon.

There is a multipart problem with the 2000 and 2010 census tract polygons; see Figure 4-1. In Figure 4-1, the number of workers (i.e., 50, 70, and 100) from CTPP are joined to a TIGER shape file based on a common ID (i.e., 1, 2, or 3). Ideally each ID indicates only one polygon on map. In reality, a single ID (i.e., 1) may indicate multiple polygons. There is no way to split the multipart polygons with their workers data without local knowledge or additional data sources. It is possible the multipart problem results from data entry error or system operation error. The problem will cause the number of employment clusters slightly underestimated, but the total number of workers in employment clusters would be unaffected.

As the population grows, the Census alters the boundaries of census tracts. This alteration is negligible. Most (more than 99.9 percent) census tracts stay the same from 2000 to 2010.

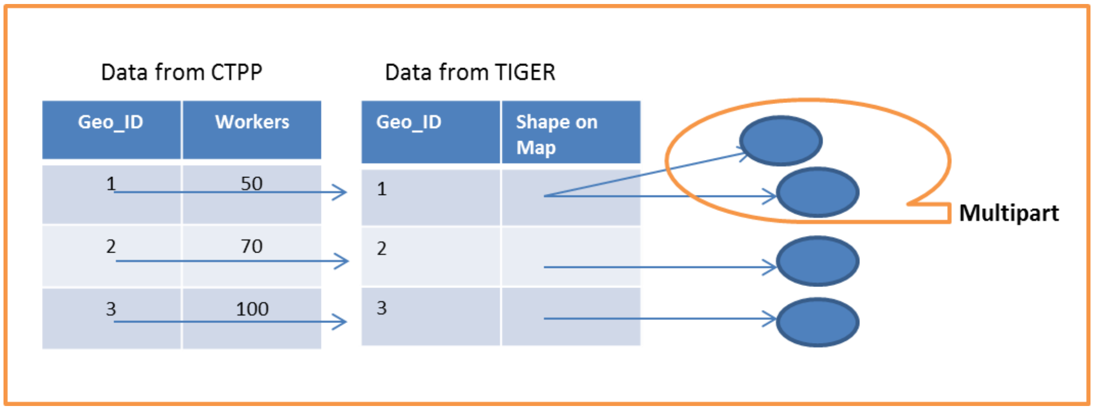


Figure 4-1 A multipart problem in TIGER shape files

4.1.2 The U.S. Census Transportation Planning Package (CTPP)

CTPP 2000 data are Excel tables containing information on respondents' commuting patterns. These tables are derived from the Census 2000 long form (Commuting) survey. CTPP 2000 includes three parts. Part 1 provides data on the residence end, part 2 on the workplace end, and part 3 on JTW flow.

I use CTPP 2000 workers' data in part 2 (by place of work) for this study. In the Census 2000 long form survey, there are 4 questions in Form D-2 (question NO. 21 to 24) asking about respondents' workplace address, time leaving for work, commuting time, and the means of transportation. Table 002 in part 2 provides the number of total workers for both sexes by all means of transportation, including working at home.

This study applies CTPP 2000 data summarized at the census tract level. CTPP 2000 provides data at multiple levels from TAZ, blockgroup, census tract to place, metropolitan area, and state. The lower the data summary level, the more accurate information the data can represent. The lowest summary level available is TAZ.

However, TAZ data are prepared by individual metropolitan agencies, thus may lack consistency. Furthermore, TAZ data are not available for all US metros; so are blockgroup level data. Therefore, census tract level data are the most accurate and consistent data that are available for all US metros.

Each of the census tract records has a geographic identification number, which can be matched with the IDs of shape file records from TIGER 2000. Joining data tables from CTPP 2000 and attribute tables (tables associated with maps) from TIGER 2000, I obtain the total number of workers for each census tract (represented by polygon) on the map.

CTPP 2006-2010 data have the same characteristics as CTPP 2000 data, except that CTPP 2006-2010 data are derived from American Community Survey (ACS) 2006-2010 5-year estimates. Census tract employment data for 2010 in this study are from CTPP 2006-2010. After 2000, the Census uses the ACS to obtain JTW data. The questionnaire is almost identical to the Census 2000 long form survey (Ruggles, 2010, available at: https://usa.ipums.org/usa/acs.shtml). Although ACS also provides 1-year and 3-year estimates, 5-year estimates have the highest precision (U.S. Census Bureau, available at: http://www.census.gov/acs/www/guidance_for_data_users/estimates/). ACS 5-year estimates are also the only source providing data at census tract level for all US metros after 2000. I use workers data at the census tract level, therefore the 2010 (2006-2010 estimates) workers data are at the same precision level with the CTPP 2000 workers data.

4.1.3 The U.S. Bureau of Economic Analysis (BEA)

There are three widely used sources for employment data by place of work--the BEA, the County Business Patterns (CBP), and the Bureau of Labor Statistics (BLS). The BEA data have the fullest employment coverage. The differences among the three sources are as follows:

> The coverage of the CBP data primarily differs from that of the BLS data because the CBP data exclude most government employees, and the BLS data cover civilian government employees…
>
> The BEA estimates of employment and wages differ from the BLS data because BEA makes adjustments to account for employment and wages not covered, or not fully covered, by the state UI and the UCFE programs. (The U.S. Bureau of Economic Analysis, available at: http://www.bea.gov/faq/index.cfm?faq_id=104#sthash.bQmeRAQK.dpuf)

The "Personal income and employment summary (CA04)" data category on the BEA website provides "Total employment" for the "Metropolitan Statistical Area" option. The metro names in the "Metropolitan Statistical Area" table match with that of the MCBSAs, except for four metros; see Table 4-1. I checked the four pairs of mismatched metros. The areas each pair denoted are the same on the map.

Table 4-1 Mismatched metro names from BEA and TIGER data

MCBSA from TIGER		MSA from BEA	
CODE	CBSA_NAME	CODE	CBSA_NAME
48260	Weirton-Steubenville, WV-OH	44600	Steubenville-Weirton, OH-WV
46940	Vero Beach, FL	42680	Sebastian-Vero Beach, FL
42260	Sarasota-Bradenton-Venice, FL	35840	North Port-Bradenton-Sarasota, FL
23020	Fort Walton Beach-Crestview-Destin, FL	18880	Crestview-Fort Walton Beach-Destin, FL

The BEA "Total employment" data are more than 25 percent larger than the JTW data in 2000 and 2010; see the coefficients in the two equations on Figures 4-2 and 4-3. The main reason is that the "BEA makes adjustments to account for employment and wages not covered, or not fully covered, by the state UI and the UCFE programs"; the "UI and the UCFE programs" refer to the "unemployment insurance (UI) program and the unemployment compensation for Federal employees (UCFE) program", respectively. (The U.S. Bureau of Economic Analysis, available at: http://www.bea.gov/faq/index.cfm?faq_id=104#sthash.1gFHSLAJ.dpuf) As the adjustment reflected in data, the "Total employment" in the "Personal income and employment summary (CA04)" category from the BEA website includes both "Wage and salary employment" by place of work and the "Proprietors employment" mostly by place of residence. Proprietors employment "is more nearly by place of residence because, for nonfarm sole proprietorships, the estimates are based on IRS tax data that reflect the addresses from which the proprietors' individual tax returns are filed, which are usually the proprietors' residences." (The U.S. Bureau of Economic Analysis, 2012, available at: http://www.bea.gov/regional/pdf/lapi2010.pdf)

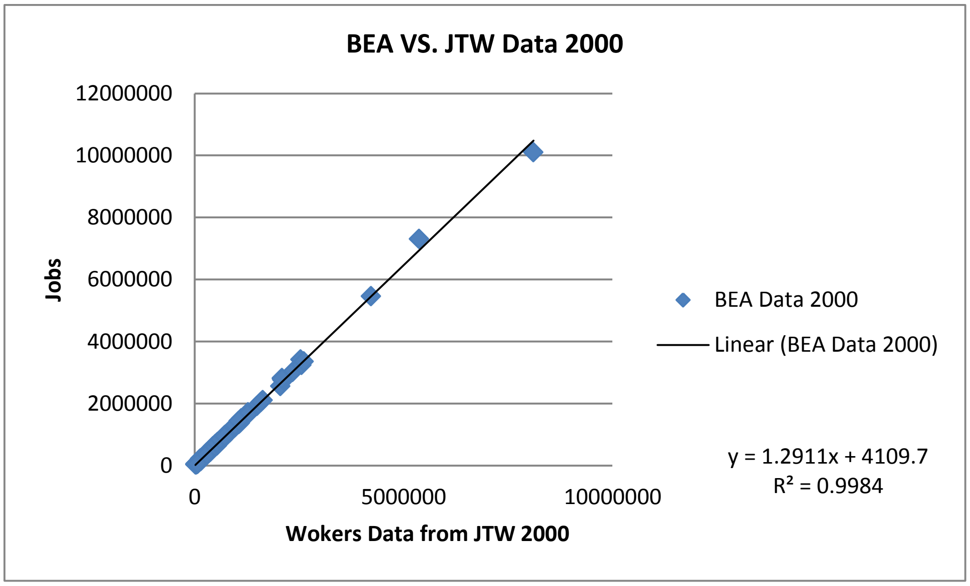


Figure 4-2 Fitting data from BEA and JTW in 2000

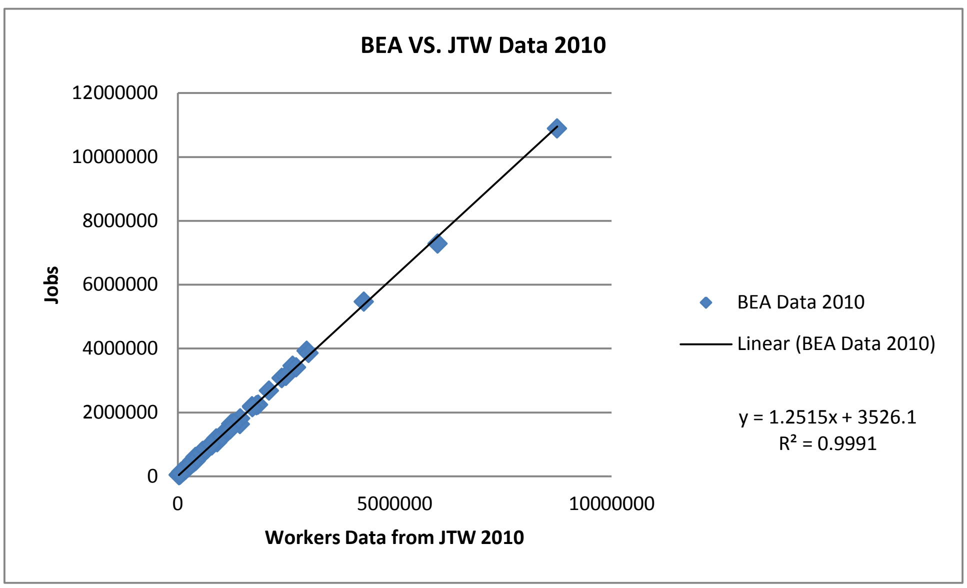


Figure 4-3 Fitting data from BEA and JTW in 2010

I use the “Total employment” data from the BEA to measure metro’s employment growth rate from 2000 to 2010 mainly for two reasons. First, the measurement of employment growth is for reflecting regional economic performance, thus it is more appropriate to apply the full employment coverage (i.e., the BEA data) than the employment data collected only at the workplace (i.e., the JTW data Part 2).

Second, the BEA data source is consistent in 2000 and 2010. The census tract employment data 2000 is from the Census 2000 long form survey, whereas the census tract employment data 2010 is from the ACS 2006-2010. Although these two data sources are similar in many ways, there are key differences that may affect the consistency of employment estimation in 2000 and 2010:

1) The sample size and timeframe are different. The Census 2000 long form survey represents an approximate 17 percent sample while the ACS 2006-2010 only represents 2 percent. Additionally, the Census 2000 long form survey collects data only in 2000 while the ACS collects data from 2006 to 2010. (Department of Transportation, available at: https://www.dot.ny.gov/divisions/policy-and-strategy/darb/dai-unit/ttss/cttp_acs)
2) The data estimation methods are different. In the Census 2000 long form survey, "the worker was asked about work in the previous week, in the ACS it is continuous recruitment and a different workplace allocation algorithm is at work when the work place is unknown as compared to the decennial census in 2000." (Department of Transportation, available at: https://www.dot.ny.gov/divisions/policy-and-strategy/darb/dai-unit/ttss/cttp_acs)

In this dissertation, I mainly use employment shares (rather than level values) to compare and contrast metros' employment distributions between 2000 and 2010, assuming employment data obtained by Census 2000 long form survey and ACS 2006-2010 reasonably represent metros' employment spatial structure characteristics for each single year.

4.2 US Metropolitan Spatial Structures and Evolution

4.2.1 Delimit Metro Urban and Rural Areas

This study uses a relative method to select the lowest employment density tracts as rural areas. This method requires a cutoff percentage to delimit urban and rural areas. Because population is generally larger than employment (especially in rural areas), I firstly tested to preserve 99 percent of employment (Wheaton chose 98 percent of population) as urban areas. However, the resulting polygons include large swathes of mountainous terrain that are clearly not urban. I secondly tested to preserve 95 percent of employment (Lee chose 95 percent of population) as urban areas. The resulting polygons, however, exclude many near urban center tracts that are clearly urban. Finally, keeping 98 percent of employment as urban areas produces a more reasonable result than using the 99 percent or 95 percent choices.

I exclude the census tract polygons with the lowest year 2000 employment density from a MCBSA until the total employment is as close to (but not less than) 98 percent of the original year 2000 total employment. The remaining census tract polygons within the MCBSA are the urban area polygons. The excluded census tract polygons are the rural area polygons where employment amounts to roughly 2 percent of the metro's total employment.

Employment data in 2000 and 2010 are allocated to the same rural area polygons. These rural area polygons are determined only by employment data in 2000. The rural areas evolution indicator reflects the rural areas employment share change from 2000 to 2010. There are four urban areas evolution indicators: the main-center, sub-centers, non-center clusters, and non-cluster urban areas. Each reflects its own employment share change from 2000 to 2010. Section 4.2.3 will describe how to separate the urban area polygons into four submetro sections.

4.2.2 Identify Employment Centers in 2000 and 2010

I use two methods to identify employment centers. The first is similar to Giuliano and Small's (1991) method. I define an employment center as a continuous area with at least 10,000 workers and a minimum density of 10 workers per acre in each census tract. Although this definition is subjective, it provides a benchmark for comparing metros across space and time. I call it the "10-10" method, for short.

The second method uses a unique density threshold for each metro, considering that US metros' employment densities vary dramatically. Then I apply a total employment threshold of 10,000 workers to separate employment centers and employment non-center clusters. Employment centers meet both the minimum density and the total employment thresholds. Employment non-center clusters only meet the minimum density threshold--they each have a total employment of less than 10,000 workers.

Each metro's density threshold equals two standard deviations above the metro's mean employment density, excluding rural areas. I call it the "2SD" method. I apply year

2000 employment data to define the unique "2SD" density threshold for each metro and use the threshold to identify the metro's employment clusters. In equation 4-1, the probability (P) is a census tract's area proportional to a metro's total urban area, P = $\sum_{i=1}^{n_j} \frac{s_{i,j}}{\sum_{i=1}^{n} s_{i,j}}$. A metro's urban average density (U) is the metro's total urban employment divided by total urban area, U = $\frac{\sum_{i=1}^{n_j} s_{i,j} d_{i,j}}{\sum_{i=1}^{n_j} s_{i,j}}$. A metro's total urban area is the sum of all urban census tract areas within the metro, S = $\sum_{i=1}^{n_j} S_{i,j}$. For metro j, we have:

$$D_j = 2 \times \sqrt{\sum_{i=1}^{n_j} \frac{s_{i,j}}{\sum_{i=1}^{n} s_{i,j}} \left(d_{i,j} - \frac{\sum_{i=1}^{n_j} s_{i,j} d_{i,j}}{\sum_{i=1}^{n_j} s_{i,j}} \right)^2} + \frac{\sum_{i=1}^{n_j} s_{i,j} d_{i,j}}{\sum_{i=1}^{n_j} s_{i,j}} \quad \text{(Equation 4-1)}$$

Where,

D_j—Metro j's density threshold; j=1, 2, 3, …, 361

$S_{i,j}$—Urban census tract i's area for metro j; i=1, 2, 3, …, n_j (n_j= metro j's total number of urban census tract)

$d_{i,j}$—Urban census tract i's density for metro j

4.2.3 Construct Structural and Evolution Indicators

Constructing a metro's five structural (or evolution) indicators involves three processes. The first process is to separate a metro into urban areas and rural areas. As previously discussed, I use the employment data in 2000 to determine the location of a metro's rural areas. The employment share in a metro's rural areas (i.e., areas that were originally rural in 2000) in 2010 might exceed 2 percent of the metro's total employment since areas that were rural in 2000 may no longer be rural in 2010. Figures 4-4 and 4-5 illustrate a metro's rural areas are defined to be the same in 2000 and 2010. The difference of employment share from 2000 to 2010 in the rural areas is the rural areas evolution indicator for this metro.

The second process is to separate a metro's urban areas into four submetro sections (i.e., the main-center, sub-centers, non-center clusters, and non-cluster urban areas); see Figure 4-4 and 4-5. I use the "2SD" method to identify a metro's employment clusters. This process includes four steps:

i. Select a metro's census tracts with employment density higher than its "2SD" threshold as eligible to construct employment clusters.
ii. Merge neighboring eligible census tracts into a zone.
iii. Define a zone with no less than 10,000 workers as an employment center; otherwise, this zone is an employment non-center cluster.
iv. Define the largest employment center as the main-center.

The third process is to calculate the evolution indicators for the four urban submetro sections. The difference in employment share of the main-center from 2000 to 2010 is the main-center evolution indicator. The difference in employment share of the sub-centers (i.e., employment centers excluding the main-center) from 2000 to 2010 is the sub-centers evolution indicator. The difference in employment share of the employment non-center clusters is the non-center clusters evolution indicator. The difference in employment share of the non-cluster urban areas (i.e., metro's urban areas excluding the main-center, sub-centers, and non-center clusters) is the non-cluster urban areas evolution indicator.

4.2.4 Clustering Metros in 2000 and 2010

Cluster analysis is a method used to identify groups of objects with similar characteristics while separating them from other groups (Mooi and Sarstedt, 2011; Everitt, 2001). A hierarchical cluster analysis typically presents a hierarchy of clusters using a dendrogram. I apply the “hclust” function in R (freeware) to perform the hierarchical clustering to group metros based on micro spatial structure types in 2000 and 2010, respectively. Further research is needed to fully understand the usefulness of the clusters in this analysis.

I employ two processes to prepare the data. In order to reduce the micro spatial structures to a manageable amount, I substitute the five employment shares by their ranks (e.g., 1, 2, 3, 4, and 5). The sequence (from the main-center, sub-centers, non-center clusters, non-cluster urban areas, to rural areas) of the ranks represents a metro’s micro spatial structure type. For example, a metro with a sequence of “54321” and a metro with a sequence of “45321” are different micro spatial structure types. For the former, its main-center employment share ranks the highest; for the latter, its sub-centers employment share ranks the highest.

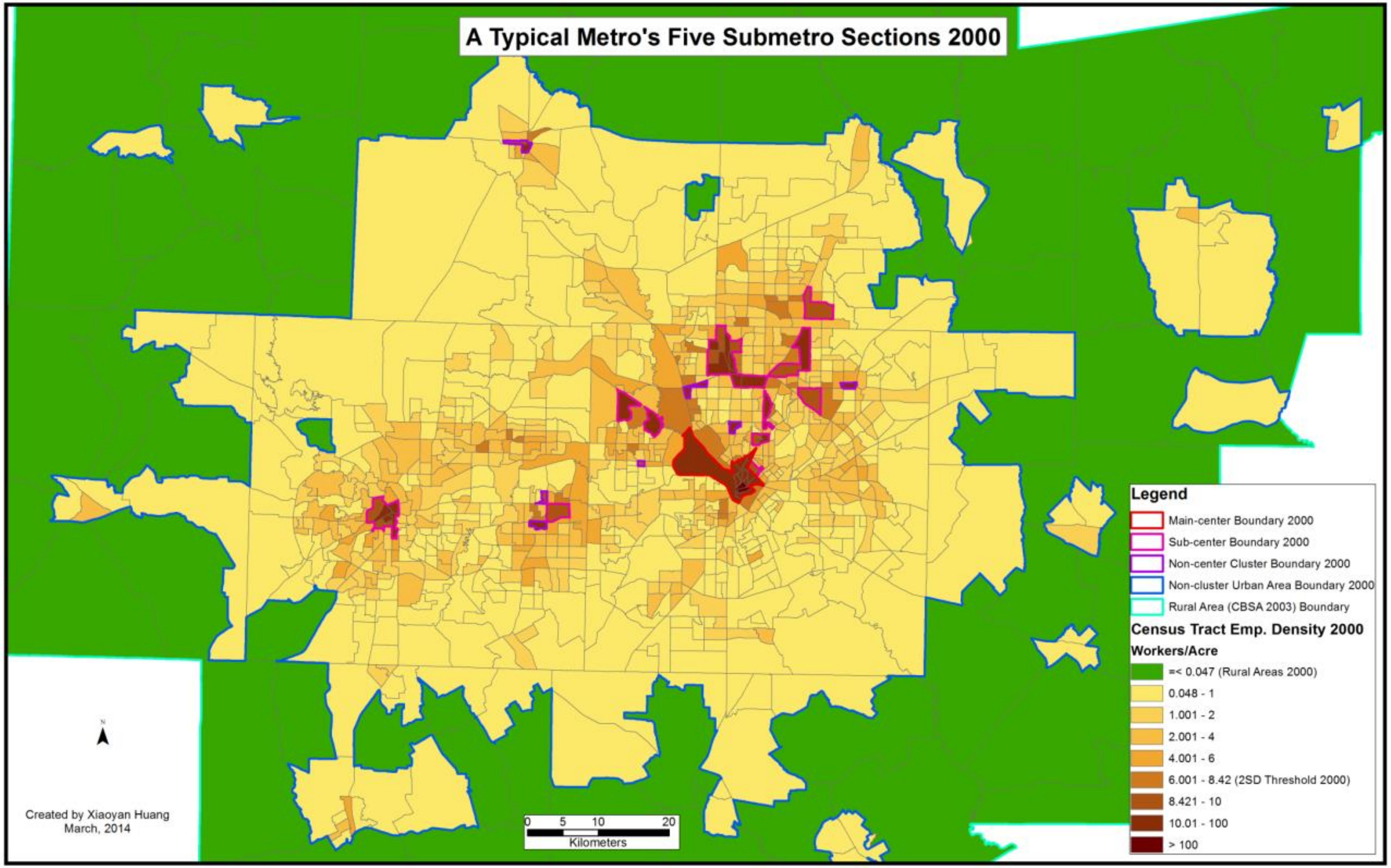


Figure 4-4 Dallas−Fort Worth−Arlington, TX in 2000

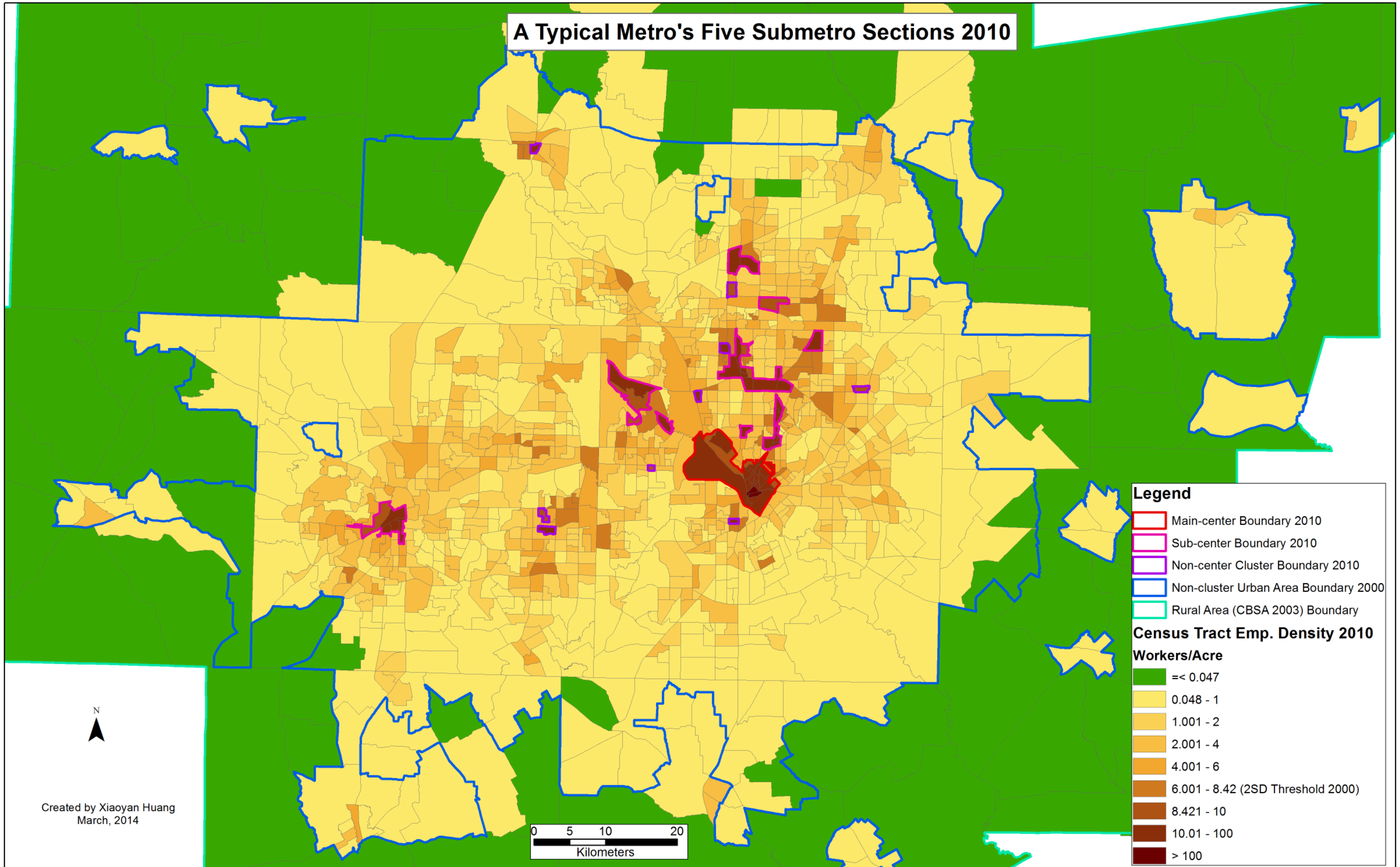


Figure 4-5 Dallas−Fort Worth−Arlington, TX in 2010

In order to ensure the three macro spatial structure types each grouped as a distinct cluster, I add weights to the number of employment centers variable. If the number of employment centers is zero (i.e., a coreless metro) then the metro will be assigned a value of “10”. If the number of employment centers is one (i.e., a monocentric metro) then the metro will be assigned a value of “20”. If the number of employment centers is greater than one (i.e., a polycentric metro) then the metro will be assigned a value of “30”. Note that the choice of the weights (i.e., 10, 20 and 30) are arbitrary as long as the differences are large enough to make coreless, monocentric, and polycentric metros three distinct groups.

Finally, I choose Ward’s method for clustering, using squared Euclidean distance. Ward’s method is based on minimum variance within group. For each step, the algorithm chooses the relatively low variance pair of variables into the group, considering the whole dataset. In this case, the variables include the metro’s macro spatial structure type and five employment shares ranks of the five submetro sections (i.e., main-center, sub-centers, non-center clusters, non-cluster urban areas, and rural areas).

4.3 Metropolitan Spatial Structure Evolution and Employment Growth

4.3.1 Two-Sample T-Test for Macro Spatial Structure Evolution

A two-sample t-test is a statistical method used to compare the means of two populations, assuming population normality (Walker, 2010). In this study, a population represents a group of metros that evolve through the same path from 2000 to 2010. I perform two-sample t-tests on the employment growth rates of metros to see if different evolution paths associate with different employment growth rates.

Table 4-2 shows group samples' normality. Among the nine possible evolution paths, five had an observation size of less than eight metros. Therefore, I conducted the two-sample t-tests only for the four groups of metros with adequate observation sizes. All four groups of metros followed a normal distribution, except the one group evolving from monocentric to polycentric. A graph box shows two outliers: 0.47 (McAllen-Edinburg-Pharr, TX) and 0.30 (Kennewick-Richland-Pasco, WA). I dropped the further outlier McAllen-Edinburg-Pharr, TX. This (monocentric to polycentric) group is therefore not statistically significant different from normal distribution at .05 significance level.

Table 4-2 Skewness and kurtosis tests for normality

Metros' evolution paths		Distribution of employment growth rate (from 2000 to 2010)				
Macro spatial structure type in 2000	Macro spatial structure type in 2010	Obs.	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	Prob>chi2
Monocentric	Monocentric	201	0.05	0.50	4.21	0.12
	Polycentric	32	0.01	0.01	11.48	0.00
		31 [a]	0.71	0.27	1.43	0.49
Polycentric	Monocentric	19	0.99	0.52	0.42	0.81
	Polycentric	97	0.15	0.95	2.11	0.35

([a] McAllen-Edinburg-Pharr, TX was removed from the monocentric to polycentric group in order to establish a normal distribution)

4.3.2 Multiple Regression for Micro Spatial Structure Evolution

Regression analysis is a statistical method used to estimate the relationship between variables (Sykes, 1993). A multiple regression analysis involves more than one independent variable. This study explores the influence of evolution indicators on employment growth rate. The control variables are the initial structural indicators and initial metro employment size. I use the STATA software to execute multiple regression analysis, along with regression diagnostic tests.

I initially included all potential independent variables in the regression model; see Table 4-3. I added and removed variables to compare the adjusted R-squared values. This trial-and-error procedure resulted in four significant independent variables; see Table 4-4.

Table 4-3 Modeling for all potential independent variables

Dependent Variable	Regional employment growth rate from 2000 to 2010 (BEA data)		Coefficient	t	P>|t|	Beta
Independent Variables	Five evolution indicators (employment share changes from 2000 to 2010)	Main-center	0.30	2.69	0.01	0.30
		Sub-centers	0.46	2.92	0.00	0.19
		Non-center clusters	0	0	-	-
		Non-cluster urban areas	-0.26	-2.00	0.05	-0.19
		Rural areas	0.59	2.78	0.01	0.16
	Five initial structural indicators (year 2000 employment shares)	Main-center	1.66	1.59	0.11	2.66
		Sub-centers	1.90	1.80	0.07	1.11
		Non-center clusters	1.47	1.41	0.16	1.20
		Non-cluster urban areas	1.48	1.39	0.17	1.80
		Rural areas	0	0	-	-
	Initial (year 2000) metro employment size		0	0	1.57	0.12

(Note: R-squared = 0.236; Adj R-squared = 0.216.)

Table 4-4 Modeling for four significant independent variables

Dependent Variable	Regional employment growth rate from 2000 to 2010 (BEA data)		Coefficient	t	P>|t|
Independent Variables	Two evolution indicators (employment share changes from 2000 to 2010)	Non-center clusters	-0.31	-2.94	0.00
		Non-cluster urban areas	-0.60	-8.79	0.00
	Two initial structural indicators (year 2000 employment shares)	Main-center	0.18	5.04	0.00
		Sub-centers	0.40	4.08	0.00

(Note: R-squared = 0.218; robust regression.)

I use two diagnostic tests to validate the model. The first diagnostic test checks for multicollinearity among independent variables to ensure their effects on the dependent variable do not significantly overlap. The Variance Inflation Factor (VIF) provides a quantitative measure of multicollinearity. As a rule-of-thumb, if the VIF is less than 10 there is no significant multicollinearity among the independent variables. As Table 4-5 shows the four independent variables are within the acceptable range.

Table 4-5 Variance inflation factor for four independent variables

Independent variables		VIF
Two evolution indicators (employment share changes from 2000 to 2010)	Non-center clusters	1.17
	Non-cluster urban areas	1.05
Two initial structural indicators (year 2000 employment shares)	Main-center	1.55
	Sub-centers	1.49

The second diagnostic test checks for heteroscedasticity—whether one independent variable will influence another's predictive power over the dependent variable. I use White's test (White, 1980) to determine whether there is statistically significant heteroscedasticity in the model. White's test regresses the squared residuals of the original model onto the original, squared, and cross products of the original independent variables. In Table 4-6, the p-value for heteroscedasticity (0.08) is larger than 0.05 (significance level). Therefore, there is no statistically significant heteroscedasticity in the model.

Additionally, the Cameron & Trivedi's decomposition of IM-test in Table 4-6 checks for the third (skewness) and fourth (kurtosis) orders of error distribution. The p-value (0.15) for kurtosis indicates the error distribution is not statistically significantly different from that of a normal distribution at 0.05 significance level. However, the p-value for skewness is smaller than 0.05, indicating the error distribution is statistically significantly skewed. The skewness is likely due to the low predictive power of the four independent variables. They only explain about 21.8 percent of the dependent variable, according to the R-squared value in Table 4-4. The factors contributing to the skewness are non-structural variables such as institutional support, labor skills, infrastructure, and entrepreneurship.

Table 4-6 White's test for heteroscedasticity

<table>
<tr><td colspan="4">White's test for H0: homoskedasticity
against Ha: unrestricted heteroskedasticity</td></tr>
<tr><td colspan="4">chi2(14) = 22.06
Prob > chi2 = 0.08</td></tr>
<tr><td colspan="4">Cameron & Trivedi's decomposition of IM-test</td></tr>
<tr><td>Source</td><td>chi2</td><td>df</td><td>p</td></tr>
<tr><td>Heteroskedasticity</td><td>22.06</td><td>14</td><td>0.08</td></tr>
<tr><td>Skewness</td><td>22.49</td><td>4</td><td>0.00</td></tr>
<tr><td>Kurtosis</td><td>2.08</td><td>1</td><td>0.15</td></tr>
</table>

In sum, two post-estimation tests show the regression model (Table 4-4) is valid. The R-squared value decreased slightly from 0.236 to 0.218, compared with the initial model (Table 4-3) containing all potential independent variables. That means, removing the other variables does little harm to the model.

CHAPTER V

A SYNTHESIS OF SPATIAL STRUCTURE CHARACTERISTICS

5.1 Structural and Evolution Indicators

5.1.1 Structural Indicators

Table 5-1 shows the cumulative structural indicators in 2000 and 2010. The cumulative employment distribution was very similar in 2000 and 2010, except that coreless metros in 2010 were highly dispersed with 11.03 percent of employment in former rural areas. In 2000 and 2010, the cumulative employment outside centers accounted for 71.33 percent and 71.95 percent of US metro total employment, respectively. This result agrees with previous studies which estimated about two-thirds to three-fourths of metro's employment is located outside of centers (Giuliano et al., 2008).

Table 5-1 Cumulative structural indicators in 2000 and 2010

Year	Macro spatial structure type	NO. of employment clusters		Employment in centers			Employment outside centers			
		Employment centers	Non-center clusters	Main-center (%)	Sub-centers (%)	Sub-total (%)	Non-center clusters (%)	Non-cluster urban areas (%)	Rural areas (%)	Sub-total (%)
2000	Coreless	0	25	0	0	0	42.65	56.24	1.12	100
	Monocentric	236	269	38.58	0	38.58	4.78	55.06	1.58	61.42
	Polycentric	418	502	16.98	9.00	25.98	2.65	69.47	1.91	74.02
	Total	654	796	21.65	7.02	28.67	3.20	66.30	1.83	71.33
2010	Coreless	0	13	0	0	0	22.34	66.64	11.03	100
	Monocentric	227	245	37.45	0	37.45	4.06	55.51	2.97	62.55
	Polycentric	466	589	16.91	8.74	25.65	2.73	68.44	3.19	74.35
	Total	693	847	21.16	6.89	28.05	3.06	65.73	3.16	71.95

Figure 5-1 shows individual structural indicators for the three macro spatial structure types. The first three rows of Figure 5-1 show the data for the coreless, monocentric, and polycentric metros, respectively. The last row shows the cumulative data from all three macro spatial structure types. Each row's left and right columns represent the data in 2000 and 2010, respectively. The employment distribution (represented by the five structural indicators) in 2000 and 2010 were very similar. Notable characteristics include:

- For coreless metros, their employment concentrated either at non-center cluster areas or at non-cluster urban areas.
- For monocentric metros, their mean main-center employment share was larger than that of coreless and polycentric metros.
- For polycentric metros, employment share was higher in non-cluster urban areas than in the main-center, except a few outliers. Second, non-center clusters' employment share was extremely low possibly due to the agglomeration of non-center clusters into sub-centers when a monocentric metro evolved to be polycentric.

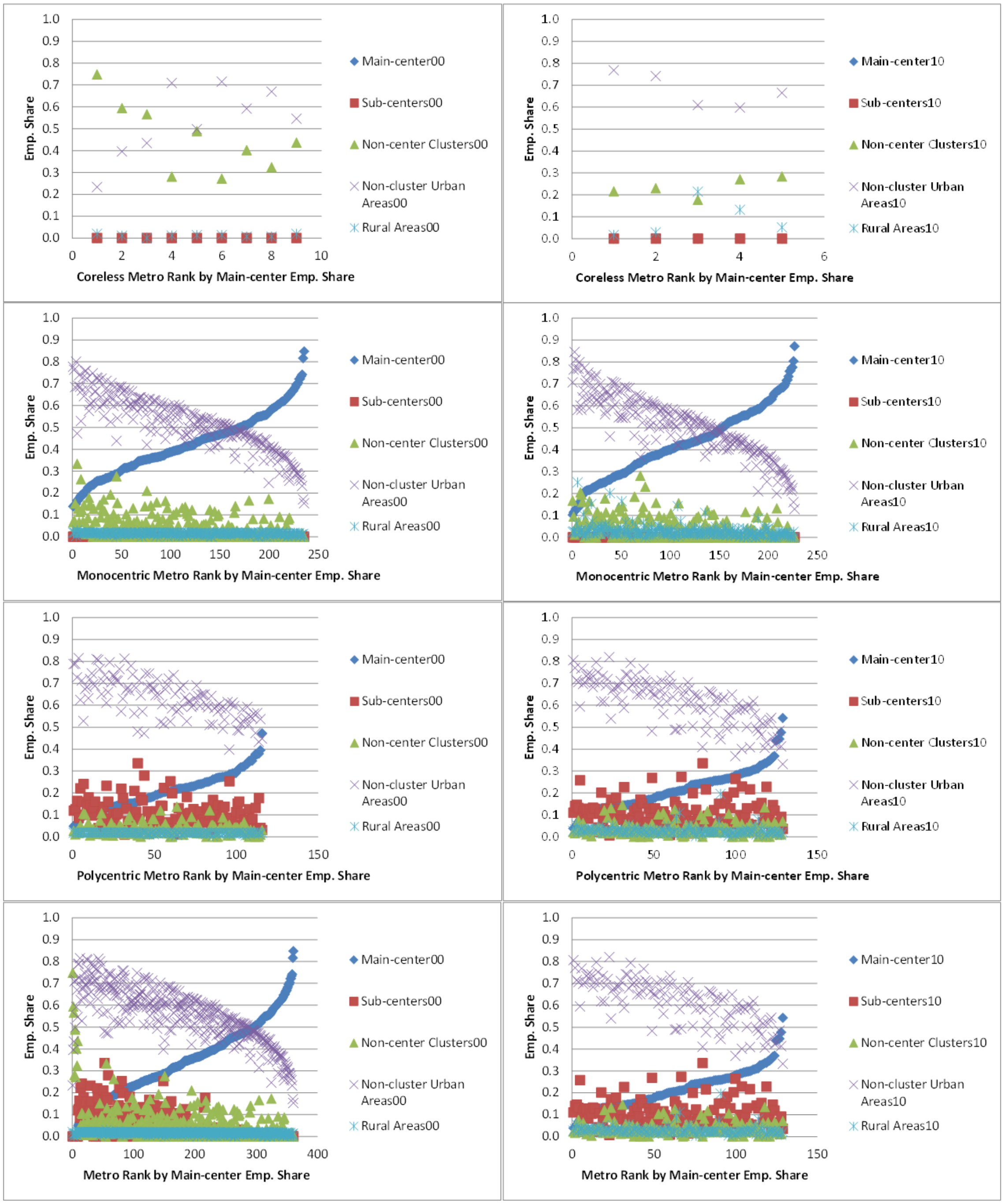


Figure 5-1 Individual structural indicators distribution in 2000 and 2010

- For monocentric and polycentric metros, non-cluster urban areas (approximately in 77 percent of metros) and main-center (approximately in 23 percent of metros) were the two dominant employment types.

Table 5-2 shows the correlations between number of clusters, structural indicators, and total employment. The correlations in 2000 and 2010 were very similar, specifically:

1) Metros with more employment centers tended to have more non-center clusters.
2) Metros with more employment centers tended to have higher sub-centers employment share, indicating employment center sizes were relatively constant.
3) Larger metros (in terms of employment) tended to have more employment centers and non-center clusters.
4) Metros with larger main-center employment share tended to have smaller non-cluster urban areas employment shares.
5) Metros with more employment centers tended to have less main-center employment share, although the correlation was not strong.

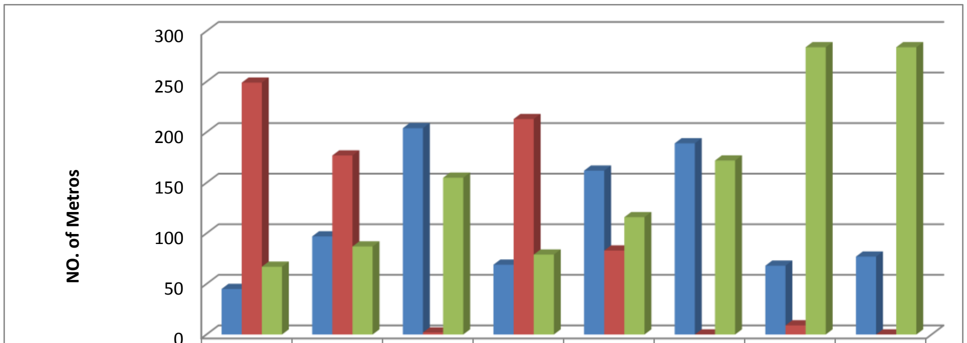
Table 5-2 Correlations between structural indicators

Year 2000	NO. of centers 2000	NO. of non-center clusters 2000	Main-center employment share 2000	Sub-centers employment Share 2000	Non-center clusters employment share 2000	Non-cluster urban areas employment share 2000	Rural areas employment share 2000	Metro total employment value 2000
NO. of centers 2000	1							
NO. of non-center clusters 2000	0.5775*	1						
Main-center employment share 2000	-0.4260*	-0.4851*	1					
Sub-centers employment Share 2000	0.6068*	0.3048*	-0.4879*	1				
Non-center clusters employment share 2000	-0.1732*	0.1616*	-0.3926*	-0.1066*	1			
Non-cluster urban areas employment share 2000	0.3732*	0.3727*	-0.8050*	0.2247*	-0.0963	1		
Rural areas employment share 2000	0.2826*	0.2641*	-0.3179*	0.2148*	-0.1113*	0.3481*	1	
Metro total employment value 2000	0.7877*	0.7459*	-0.3341*	0.2603*	-0.1074*	0.3758*	0.2493*	1
Year 2010	NO. of centers 2010	NO. of non-center clusters 2010	Main-center employment share 2010	Sub-centers employment Share 2010	Non-center clusters employment share 2010	Non-cluster urban areas employment share 2010	Rural areas employment share 2010	Metro total employment value 2010
NO. of centers 2010	1							
NO. of non-center clusters 2010	0.6341*	1						
Main-center employment share 2010	-0.4049*	-0.4205*	1					
Sub-centers employment Share 2010	0.5067*	0.2758*	-0.4734*	1				
Non-center clusters employment share 2010	-0.1108*	0.2058*	-0.3248*	-0.0475	1			
Non-cluster urban areas employment share 2010	0.3239*	0.3237*	-0.8787*	0.1740*	0.0391	1		
Rural areas employment share 2010	0.0099	0.0427	-0.2681*	-0.0367	0.1107*	0.1068*	1	
Metro total employment value 2010	0.8183*	0.7789*	-0.3428*	0.2238*	-0.0977	0.3596*	0.0513	1

(* indicates a statistically significant correlation at 0.05 significance level; numbers in highlighted cells indicate strong correlations—correlation coefficient > 0.5)

5.1.2 Evolution Indicators

Figure 5-2 shows the cumulative changes (over all metros) in number of clusters, evolution indicators, and total employment. Figure 5-2 shows three characteristics. First, metros' employment centers were more stable than non-center clusters with 249 metros retaining their original (year 2000) number of employment centers versus only 177 metros retaining their original number of non-center clusters. Correspondently, the sub-centers structural indicator was also more stable than non-center clusters structural indicator with 213 metros retaining their original employment share in sub-centers versus only 83 metros retaining their original employment share in non-center clusters. Second, both sub-centers and non-center clusters structural indicators were more stable than the main-center, non-cluster urban areas, and rural areas structural indicators. Third, main-center and non-cluster urban areas structural indicators declined whereas rural areas structural indicators increased.



	NO. of Emp. Centers	NO. of Non-center Clusters	Main-center Structural Indicator	Sub-centers Structural Indicator	Non-center Clusters Structural Indicator	Non-cluster Urban Areas Structural Indicator	Rural Areas Structural Indicator	Metro's Total Emp.
Negative change	45	97	204	69	162	189	68	77
Zero change	249	177	2	213	83	0	9	0
Positive change	67	87	155	79	116	172	284	284

Figure 5-2 Cumulative changes of all metros from 2000 to 2010

Figure 5-3 shows the individual change (per metro) in number of clusters, evolution indicators, and total employment. Each figure plots data from the lowest to the highest values. Note that a specific rank number may not always represent the same metro. Figure 5-3 shows three major characteristics. First, the range of change for the number of centers was smaller than that for non-center clusters, confirming centers were more stable than non-center clusters. Second, main-center structural indicators had the largest range of change whereas rural areas structural indicators had the smallest range of change, among all evolution indicators. Third, most metros (73 percent) had a minor increase in total employment, with only 22 metros having substantive growth (over 100,000 workers).

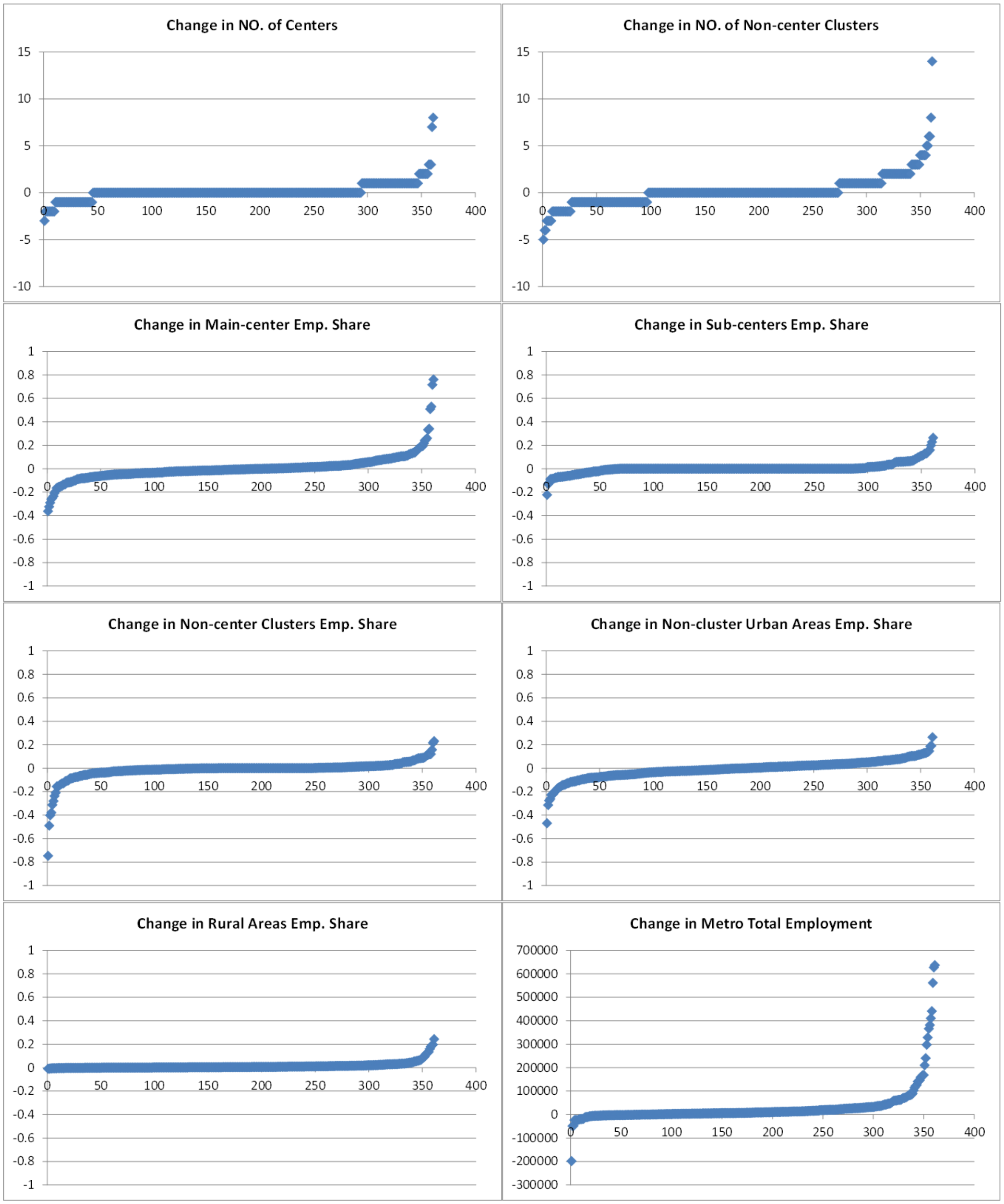


Figure 5-3 Individual metro's changes from 2000 to 2010

Figure 5-4 shows the change in employment center locations from 2000 to 2010. Most employment centers remained in their original locations while others slightly shifted due to uneven urban development. However, some employment centers in the northeast part of the US completely disappeared possibly due to the migration of employment out of the metros.

Table 5-3 shows the correlation between number of clusters, evolution indicators, and total employment. The results show a strong negative correlation between main-center employment share change and non-cluster urban areas (or non- center clusters) employment share change.

The following equation models the strong negative correlation between the main-center and non-cluster urban areas evolution indicators.

$$\frac{MC_0+A}{M_0+A+B+C} - \frac{MC_0}{M_0} = -k\left(\frac{Urb_0+B}{M_0+A+B+C} - \frac{Urb_0}{M_0}\right) \; (k > 0) \quad \text{(Equation 5-1)}$$

Where,

M_0—initial metro total employment;

MC_0—initial main-center employment;

Urb_0—initial non-cluster urban areas employment;

A—employment change in main-center;

B—employment change in non-cluster urban areas;

C—employment change in the other three submetro sections;

k—coefficient between main-center evolution indicator and non-cluster urban areas evolution indicator.

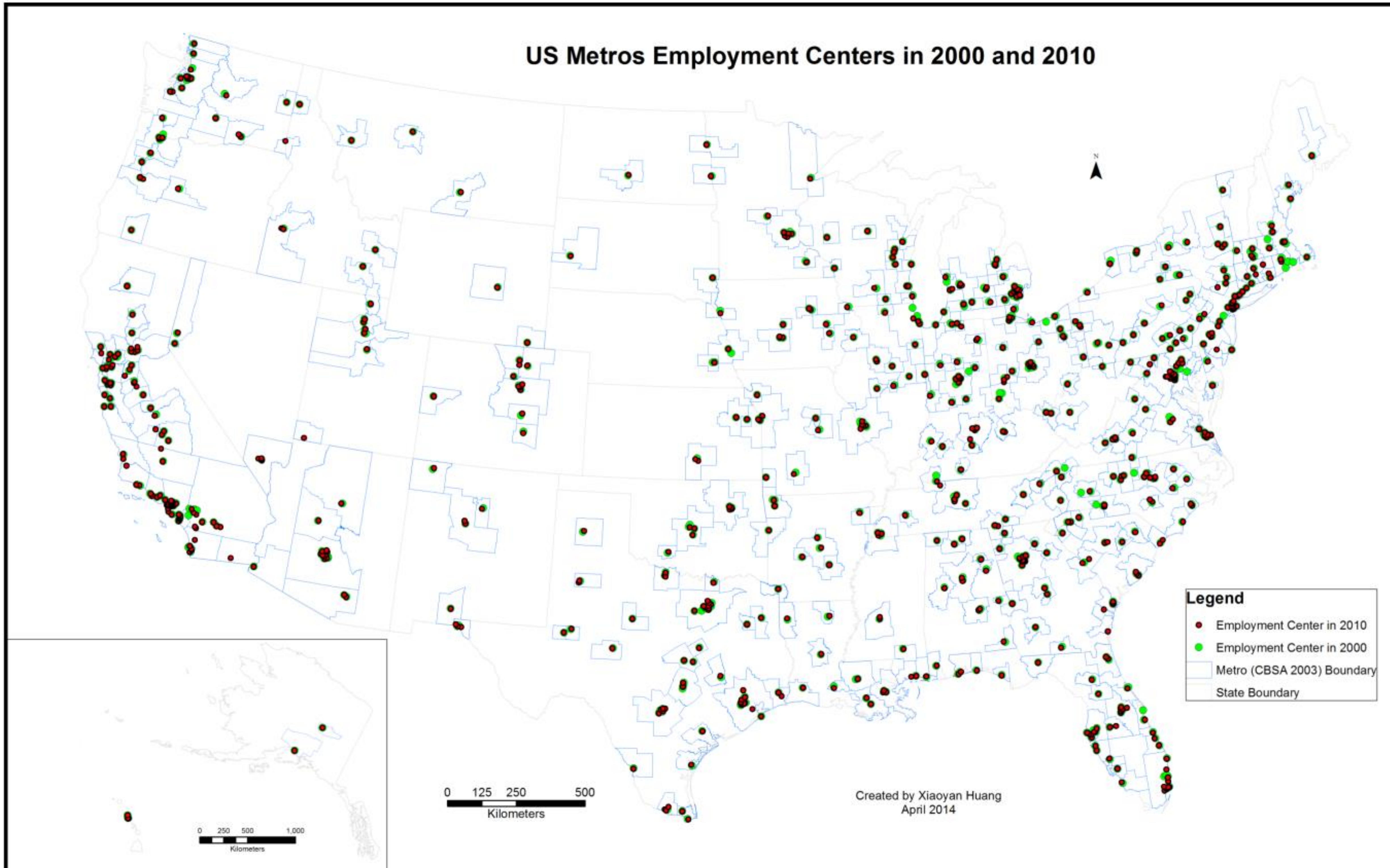


Figure 5-4 US metros employment centers in 2000 and 2010

Table 5-3 Correlations between evolution indicators

Change from 2000 to 2010	Change in NO. of centers	Change in NO. of non-center clusters	Change in main-center employment share	Change in sub-centers employment share	Change in non-center clusters employment share	Change in non-cluster urban areas employment share	Change in rural areas employment Share	Change in metro total employment value
Change in NO. of centers	1							
Change in NO. of non-center clusters	0.1526*	1						
Change in main-center employment share	0.0557	-0.1285*	1					
Change in sub-centers employment share	0.5198*	-0.1441*	-0.1456*	1				
Change in non-center clusters employment share	-0.1817*	0.3788*	-0.6482*	-0.0955	1			
Change in non-cluster urban areas employment share	-0.1665*	-0.0887	-0.5947*	-0.2457*	-0.0191	1		
Change in rural areas employment Share	-0.0759	-0.0684	-0.1587*	-0.0858	-0.0544	-0.0556	1	
Change in metro total employment value	0.4861*	0.4463*	0.0343	-0.0123	0.0171	-0.0664	0.0247	1

(* indicates a statistically significant correlation at 0.05 significance level; numbers in highlighted cells indicate strong correlations—correlation coefficient > 0.5.)

Because $k > 0$, rewrite Equation 5-1 as the following inequality:

$$\left(\frac{\boldsymbol{A}}{\boldsymbol{CBD_0}} - \frac{\boldsymbol{A+B+C}}{\boldsymbol{M_0}}\right)\left(\frac{\boldsymbol{B}}{\boldsymbol{Urb_0}} - \frac{\boldsymbol{A+B+C}}{\boldsymbol{M_0}}\right) < \mathbf{0} \qquad \text{(Equation 5-2)}$$

Where,

$\frac{A}{MC_0}$—employment growth rate in main-center;

$\frac{B}{Urb_0}$—employment growth rate in non-cluster urban areas;

$\frac{A+B+C}{M_0}$—employment growth rate in the metro.

Equation 5-2 implies if the main-center employment growth rate is larger than regional employment growth rate then the non-cluster urban areas (or non-center clusters) employment growth rate must be smaller than regional employment growth rate and vice versa. Similarly, the strong positive correlation between sub-centers evolution indicator and change in number of centers implies the sub-centers employment growth rate must be larger than the regional employment growth rate if the metro's number of employment centers increases.

5.2 US Metropolitan Spatial Structure

Table 5-4 provides a summary of metros macro spatial structure types in 2000 and 2010. Both the "10-10" and the "2SD" methods showed the majority of US metros were not polycentric in 2000 and 2010. The "10-10" method showed the majority of US metros have been coreless since 2000 (52.6 and 51.25 percent of US metros in 2000 and 2010 respectively). The "2SD" method showed the majority of US metros have been monocentric since 2000 (65.37 and 62.88 percent of US metros in 2000 and 2010, respectively). Therefore, one can conclude the US has never entered a polycentric era since 2000.

Table 5-4 Summary of metro macro spatial structure types in 2000 and 2010

Year	Total metros	10-10 Method			2SD Method		
		Coreless	Monocentric	Polycentric	Coreless	Monocentric	Polycentric
2000	361	190	111	60	9	236	116
	100%	52.6%	30.7%	16.6%	2.5%	65.4%	32.1%
2010	361	185	119	57	5	227	129
	100%	51.25%	32.96%	15.79%	1.39%	62.88%	35.73%

The “2SD” method has two advantages over the “10-10” method because of the density threshold. First, the “2SD” method uses a unique density threshold for each metro, accounting for the large variation in US metros’ employment density. Second, the “2SD” method calculates the unique density threshold based on current Census data whereas the “10-10” method sets a global threshold based on previous “expert opinion.” These “expert opinions” have no quantitative basis and are quickly becoming obsolete due to technological advances in transportation. For example, consider the area of agglomeration economies measured by a circle with a radius of 30 minutes by either walking or driving. The former (walking) will expand to a smaller area than the latter (driving) to conduct necessary economic activities. The former will result in a higher employment density than the latter to take advantages of agglomeration economies (other things being equal).

There were 22 (and 25) micro spatial structure types in 2000 (and 2010). Appendix 1 shows each metro's micro spatial structure type. In the third and fourth columns, "C", "M", and "P" denote Coreless, Monocentric, and Polycentric, respectively. "0", "1", "2", "3", "4", and "5" indicate the rank of employment shares in a metro; the higher the rank number, the larger the employment share. "0" means at least two employment shares have a zero value. For example, M40053 means this group of metros are monocentric; its main-center ranks 4th in employment share; its sub-centers, and non-center clusters employment shares are all zero; its non-cluster urban areas employment ranks 5th; and its rural employment share ranks 3rd. The most common micro spatial structure types were M41352, M40053, P43251 and M50043 in 2000 and 2010. Approximately 77 and 23 percent of metros had their largest employment shares in non-cluster urban areas and main-centers, respectively.

5.3 US Metropolitan Spatial Structure Evolution

5.3.1 Macro Spatial Structure Evolution

Table 5-5 shows a summary of metros macro spatial structure evolution paths. The results show 22 percent of coreless metros remained coreless, 85 percent of monocentric metros remained monocentric, and 84 percent of polycentric metros remained polycentric. Therefore, monocentric and polycentric metros were more stable than coreless metros. There was no coreless metro evolving to be polycentric and vice versa. A monocentric structure seems to be the intermediate stage of a metro evolving from coreless to polycentric.

Table 5-5 Metros' macro spatial structure evolution paths

Metros' macro spatial Structure type in 2000		Metros' macro spatial structure type in 2010		Percentage of evolution
Group name	NO. of metros	Group name	NO. of Metros	
Coreless	9	Coreless	2	22%
		Monocentric	7	78%
Monocentric	236	Coreless	3	1%
		Monocentric	201	85%
		Polycentric	32	14%
Polycentric	116	Monocentric	19	16%
		Polycentric	97	84%

Figure 5-5 shows the locations of metros in each evolution path. Metros evolving to be or remaining coreless had extremely small areas and were located mostly in the eastern part of the US. Polycentric metros remaining polycentric were located mostly in the eastern part and west coast of the US. Metros evolving from polycentric to monocentric were also located mostly in the eastern part of the US.

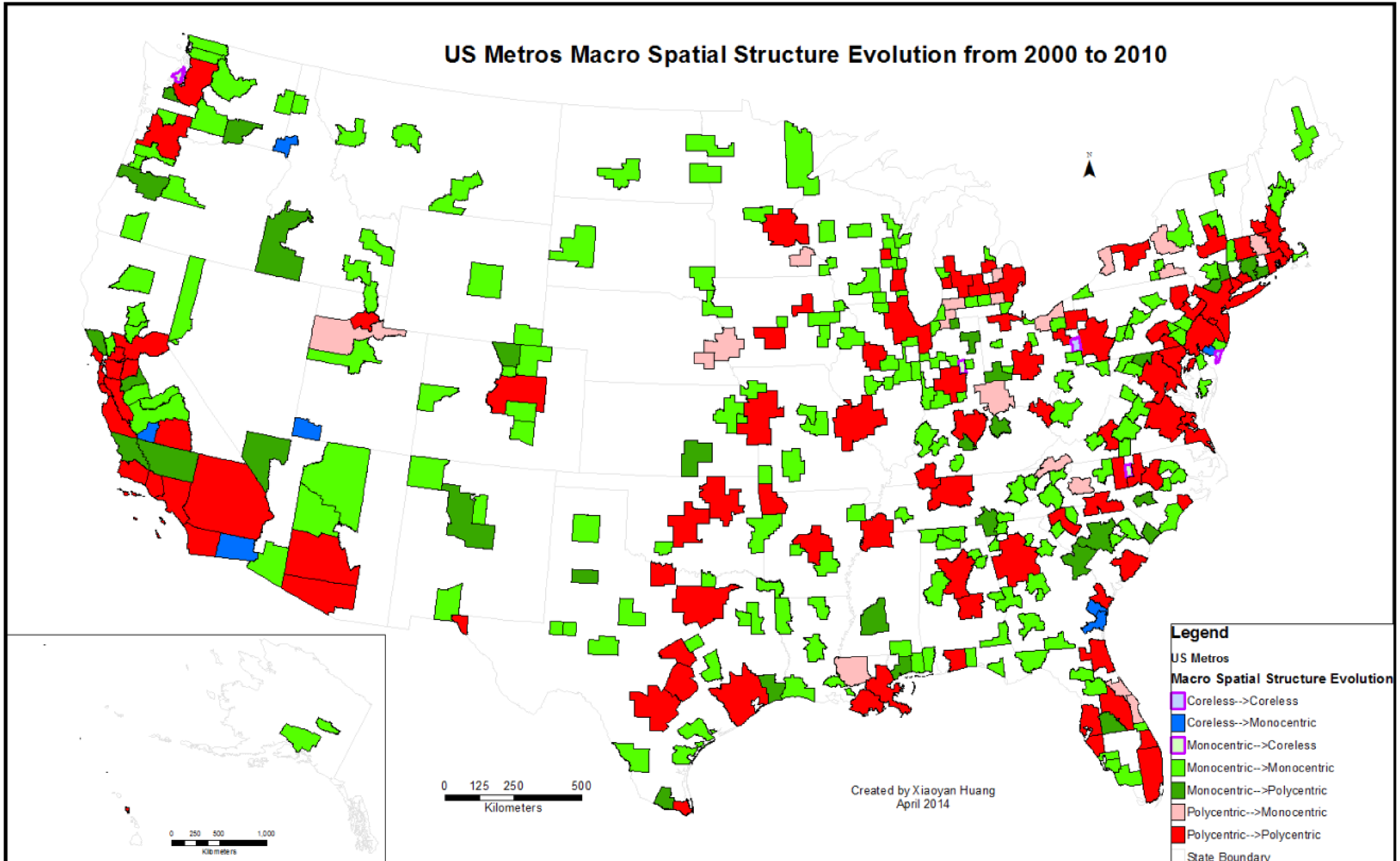


Figure 5-5 US metros macro spatial structure evolution from 2000 to 2010

5.3.2 Micro Spatial Structure Evolution

There were 101 micro spatial structure evolution paths, consisting of 22 and 25 micro spatial structure types in 2000 and 2010, respectively. Most (16 out of the 22) micro spatial structure types remained the same from 2000 to 2010. The most stable metro types were also the most common metro types in 2000 and 2010; see Table 5-6.

Table 5-6 Most stable micro spatial structure types in the US

Micro spatial structure types	NO. of metros in 2000	NO. of metros in 2010	Percentage of evolution
M41352	87	41	47%
M40053	54	30	56%
P43251	49	24	49%
M50043	42	24	57%

Table 5-7 shows the association between main-center employment share ranking and macro spatial structure evolution. The results show metros with low (2nd and 3rd) main-center employment share ranking were more likely to remain in their macro spatial structure type than metros with high (4th and 5th) or zero main-center employment share ranking. Furthermore, polycentric metros with higher main-center employment share ranking were more likely to evolve to monocentric, indicating that the stronger the main-center, the more likely for the sub-centers to disperse.

Note that coreless metros have no main-center, therefore their main-center employment share ranks zero. Monocentric metros have no sub-center and a very small amount of rural-area employment, therefore monocentric metros' main-center employment share ranking starts at 3rd, following sub-centers and rural areas. Similarly, polycentric metros have a very small amount of rural-area employment, therefore polycentric metros' main-center employment share ranking starts at 2rd, following rural areas.

Table 5-8 shows the association between main-center employment share ranking and its possibility of change. The results show metros in each macro spatial structure type with higher main-center employment share ranking were more likely to decrease in rank. Furthermore, only 32 of the 361 metros decreased in main-center employment share ranking, indicating employment decentralization was not prevalent from 2000 to 2010.

Table 5-7 Employment decentralization and macro spatial structure evolution

Metros in 2000			Metros in 2010	
Macro spatial structure type	Main-center employment share		Macro spatial structure type	Percentage of evolution
	Rank	Number		
Coreless	Zero	9	Coreless	33.33%
			Monocentric	66.67%
Monocentric	3rd	3	Monocentric	100.00%
	4th	154	Coreless	1.95%
			Monocentric	81.17%
			Polycentric	16.88%
	5th	79	Monocentric	92.41%
			Polycentric	7.59%
Polycentric	2nd	1	Polycentric	100.00%
	3rd	22	Monocentric	4.55%
			Polycentric	95.45%
	4th	92	Monocentric	18.48%
			Polycentric	81.52%
	5th	1	Monocentric	100.00%

(Note: Percentages in highlighted cells indicate the macro spatial structure type remained the same from 2000 to 2010)

Table 5-8 Employment decentralization and its possibility of change

Metros in 2000			Metros in 2010	Percentage of change
Macro spatial structure type	Main-center employment share		Change in main-center employment share ranking	
	Rank	Number		
Coreless	Zero	9	No change	22.22%
			Increase	77.78%
Monocentric	3rd	3	No change	66.67%
			Increase	33.33%
	4th	154	Decrease	1.95%
			No change	82.47%
			Increase	15.58%
	5th	79	Decrease	25.32%
			No change	74.68%
Polycentric	2nd	1	Increase	100.00%
	3rd	22	Decrease	4.55%
			No change	59.09%
			Increase	36.36%
	4th	92	Decrease	7.61%
			No change	92.39%
	5th	1	Decrease	100.00%

(Note: Percentages in highlighted cells indicate the rank of main-center employment share in each macro spatial structure type decreased from 2000 to 2010)

5.4 Spatial Structure Evolution and Employment Growth Results

At the macro level, the result shows polycentric metros remaining polycentric had statistically significantly higher employment growth rates than polycentric metros evolving to be monocentric. Conversely, monocentric metros remaining monocentric or evolving to be polycentric had no statistically significant difference in employment growth rates; see Table 5-9.

Table 5-9 Two-sample t-tests assuming unequal variances

Regional employment growth rates from 2000 to 2010 (EGR00_10)	EGR00_10 (monocentric to monocentric)	EGR00_10 (monocentric to polycentric)
Mean	0.055	0.068
Variance	0.011	0.008
Observations	201	31
t Stat	-0.678	
P(T<=t) one-tail	0.251	
Regional employment growth rates from 2000 to 2010 (EGR00_10)	EGR00_10 (polycentric to monocentric)	EGR00_10 (polycentric to polycentric)
Mean	0.005	0.061
Variance	0.008	0.009
Observations	19	97
t Stat	-2.473	
P(T<=t) one-tail	0.010	

Recall, the difference between a monocentric and a polycentric metro is the presence of sub-center(s). This result implies that gaining sub-center(s) does not significantly change regional employment growth rate whereas losing sub-center(s) does. In other words, employment decentralization does not necessarily lower regional employment growth rate whereas dispersing sub-centers does.

At the micro level, the regression result shows sub-centers initial employment share has a larger positive effect on regional employment growth rate than the main-center while change in non-cluster urban areas employment share has a larger negative effect on regional employment growth rate than that in non-center clusters employment share; see Equation 5-3.

$$EGR_{00\_10} = 0.18MainCenter_{00} + 0.4SubCenters_{00} - 0.31NonCenterClusters_{00\_10} - 0.6NonClusterUrbanAreas_{00\_10} - .03 \qquad \text{(Equation 5-3)}$$

Where,

EGR_{00_10}—Regional employment growth rate from 2000 to 2010;

$MainCenter_{00}$—Main-center employment share in 2000;

$SubCenters_{00}$—Sub-centers employment share in 2000;

$NonCenterClusters_{00\_10}$—Employment share change in non-center clusters from 2000 to 2010;

$NonClusterUrbanAreas_{00\_10}$—Employment share change in non-cluster urban areas from 2000 to 2010.

Recall that employment centers meet with both high density and large size requirement. Second, the main-center is larger in size than the sub-centers; the main-center employment share accounted for about 17 percent of metro total while the sub-centers accounted for about 9 percent. Third, the non-center clusters are smaller (less than 10,000 workers) in size than sub-centers (more than 10,000 workers). Fourth, the non-center clusters are higher in density than the non-cluster urban areas. Therefore, the regression result implies:

1) Agglomeration economies exist in high density large size submetro sections (i.e., main-center and sub-centers);

2) Larger employment center does not result in higher regional employment growth rate;
3) The size of an employment cluster may change the direction of influence on regional growth rate, and
4) Lower employment density results in lower regional employment growth rate.

CHAPTER VI

DISCUSSION

6.1 Discussion on Spatial Structure

This study showed the majority of US metros were monocentric in 2000 and 2010. One of the main reasons scholars (e.g., Garreau, 1991; Bogart and Ferry, 1999) concluded the US was entering a polycentric era may be due to a lack of data. The Census did not provide full coverage of micro-level (e.g., Census tract) spatial data until the year 2000. Furthermore, the total number of metros in case studies cover less than 10 percent of total US metros with large cities such as Los Angeles, San Francisco and Chicago being the primary subjects of numerous studies. The repeated analysis of the same cities results in biased results regarding the polycentricity of the US as a whole.

At the micro level, the study found the aggregate employment share of sub-centers accounted for about 9 percent of US metro total while that of the non-cluster urban areas accounted for about 90 percent (Table 5-1). This result agrees with the "edgeless city" viewpoint. Note that monocentric and coreless metros have no sub-centers. Additionally, note that only about 23 percent of metros had their main-center employment share rank the highest while 77 percent of metros had their non-cluster urban areas employment share rank the highest.

Furthermore, the aggregate non-center clusters' employment share accounted for only about 3 percent of US metro total, indicating that the structural features previously reported to describe such concepts as "trading places" (Bogart, 2006) and "beyond polycentricity" (Gordon and Richardson; 1996) were not evident in all US metros. The most common micro spatial structure types in the US were M41352, M40053, M50043 and P43251 in 2000 and 2010, indicating many (over 1/3) metros were without non-center clusters (i.e., M40053 and M50043).

6.2 Discussion on Spatial Structure Evolution

The study found over 80 percent of metros remained in their macro spatial structure types (i.e., monocentric, polycentric, and coreless) and there were no polycentric metros evolved to be coreless (or vice versa). These findings indicate (1) metros' macro spatial structure types are very stable and (2) a metro's monocentric structure is the intermediate stage of the metro evolving from coreless to polycentric. This finding disagrees with Gordon and Richardson's (1996) claim that polycentricity is the intermediate stage of a metro evolving from monocentric to coreless. The main reason for this discrepancy is that Gordon and Richardson (1996) "identifies activity centers in terms of their trip-generating potential... [a]ctivities are more dispersed than jobs are, and total trips are more diffuse than are work-trips." (p.291) As a result, they found sub-centers in polycentric Los Angeles dispersed throughout the study period (i.e., 1970, 1980, and 1990).

This study found larger metros (in terms of the employment size) tended to have more employment centers, supporting previous claims by Fujita and Ogawa (1982) and McMillen and Smith (2003). As total US metro employment increased, the number of employment centers increased too. Although the results showed that a monocentric metro and a polycentric metro could evolve to one another with approximately the same probability, the net increase in the number of employment centers resulted in net increase in the number of polycentric metros. Therefore, the pace of monocentric metros evolving to be polycentric may be determined by the total US metro employment growth rate, assuming barrier-free workers' migration (note that the number of coreless metros was too small to have any influence on this relationship).

At the micro level, the study found sub-centers were extremely stable in number, size (proportionate to the metro size), and location. This result agrees with Giuliano et al. (2008) and Redfearn (2009) that Los Angeles employment sub-centers persisted over decades. However, Cervero et al. (2010) found that San Francisco's employment sub-centers (i.e., ECs - Edge Cities) changed in different directions in the 1990s—"[e]dge cities themselves have polarized into two groups: growing suburban ECs and declining suburban ECs." (p.15)

Therefore, different study areas may lead to different results regarding employment sub-center dynamics. The reason may lie in each metro's different growth patterns or each study's different sub-center identification method. For example, Giuliano et al. (2008) and Redfearn (2009) concluded that Los Angeles sub-centers were stable in the 1990s while Gordon and Richardson (1996) found them dispersing using a different identification method for employment centers.

Regarding employment decentralization, Giuliano et al. (2008) reviewed relevant literature from the post-world war II to 2000 and summarized:

> Long-term trends of population and employment decentralization and deconcentration within metropolitan areas are evident through 2000. Population

> and employment growth rates are higher in the suburbs than in central cities, so the central city shares of both declined. However, there is some evidence that the trend has slowed down in recent decades.

This study found the decentralization trend has almost stopped. Although the cumulative main-center employment share decreased from 21.65 to 21.16 percent of metro total, this study concluded that employment decentralization is no longer a significant factor causing micro structure change. Two more results in this study support the previous statement. First, only 32 of the 361 metros decreased in main-center employment share rank. Second, metros (of all three macro spatial structure types) with lower ranking main-center employment share were more likely to increase in rank and vice versa. That means, the main-center employment share will increase once it reaches a minimum (which varies based on the specific city).

6.3 Discussion on Spatial Structure and Agglomeration Economies

In literature, supporters for polycentric metros mainly emphasize commuting advantages (Richardson, 1988) such as short trips. They believe sub-centers provide a small area balance in housing and jobs (Giuliano, 1991; Dubin, 1991), resulting in positive externalities through labor pooling. Lin et al. (2012) summarizes:

> The urban formation mechanisms of suburbanization and polycentric centres have successfully reduced commuting trips and transport congestion in some mega cites. Polycentric urban structure has altered roadway demand to routes with less congestion and away from the traditional central business district (CBD) core of a metropolitan area. With industry and services dispersing to the suburbs

> and polycentric centres, the labour force follows, which allows many workers to enjoy less commuting distances and travel times, thereby resulting in reduced congestion in a metropolitan area's CBD. p.8

On the other hand, supporters for monocentric metros argue that monocentric metros benefit from increasing returns to scale from the large labor market (Ihlandfeldt, 1997; Goldner, 1955; Prud'homme, 1996; Bertaud, 2004) while polycentricity results in labor market fragmentation (Bertaud, 2004). Furthermore, economic performance may decline due to mismatch arising from non-transportation factors such as information limitations, racial discrimination, and weak skills (Holzer et al., 1994; Ihlanfeldt, 1997; Stoll et al., 2000).

The results from this study support both viewpoints. The study found monocentric metros evolving to be polycentric had no significant difference in regional employment growth rate when comparing with monocentric metros that remained monocentric. That means the advantages and disadvantages of a monocentric metro evolving to be polycentric may have equal effects on employment growth rate.

At the micro level, this study reveals four relationships between spatial structure (evolution) and regional employment growth rate:

1) Initial employment shares in main-center and sub-centers are positively associated with regional employment growth rate, indicating agglomeration economies exist in high-density large-size submetro sections.
2) Initial employment share in sub-centers has a larger positive effect on regional employment growth rate than that in main-center employment share, although the

former is generally smaller than the latter. This indicates a large employment center (the main-center) is not necessarily more influential than small ones (sub-centers) in increasing regional employment growth rate.

3) Initial sub-centers employment share and the increase in non-center clusters (or non-cluster urban areas) employment share have opposite effect on regional growth rate. Note that sub-centers each have larger size than each non-center cluster. That means large size submetro sections may result in positive effects on regional growth rate while small size may result in negative. Similarly, sub-centers each have higher density than each non-cluster urban area. That means high density submetro sections may result in positive effects on regional growth rate while low density may result in negative.
4) Increase in non-cluster urban areas employment share has a larger negative effect on regional employment growth rate than that in non-center clusters employment share. Note that non-cluster urban areas have lower density than non-center clusters. This result indicates lower employment density areas are more influential in decreasing regional employment growth rate.

These four relationships indicate (1) a sub-center has the most effective density and size to positively influence regional growth rate while (2) larger size (i.e., the main-center) results in lower positive effect, and (3) lower density (i.e., non-cluster urban areas) and smaller size (i.e., non-center clusters) result in negative effect on regional employment growth rate. These findings offer a more precise version of the classic urban economic theory that high density (or large size) of an agglomeration unit (e.g., employment center, urban center, local market) results in agglomeration economies, but too high a density (or large size) results in agglomeration diseconomies (Zheng, 2001; Wheeler, 2003; Lee and Gordon, 2007; Matsuo, 2008).

However, density is a relative term. The threshold of high density may be different due to local conditions (e.g., labor accessibility). If an area has high accessibility, the density can reach very high levels before it causes agglomeration diseconomies. On the other hand, if an area has low accessibility, a moderate density may result in congestion—thus dispersion becomes a better option for growth.

In summary, monocentric metros evolving to be polycentric increases regional employment growth rate, as long as employment dispersion is well managed. It is not monocentricity or polycentricity that affects employment growth rate but rather employment dispersion.

CHAPTER VII

CONCLUSIONS

7.1 Research Summary

Previous case studies on metropolitan spatial structure mainly separate a metro into employment centers and non-center areas. However, to capture agglomeration economies, employment non-center clusters are necessary. If we look at the various methods used to identify employment centers, almost every study uses a threshold (e.g. 10, 000 workers) to separate employment clusters into centers and non-center areas. However, delineated as such, these non-center areas may end up including both high-density small size clusters (i.e., non-center clusters) and the low-density urban employment (i.e., non-cluster urban areas). This, however, removes the opportunity to study separately the potential influence of each of these (i.e., non-center clusters and non-clusters) on employment change across the metro area.

The non-center clusters are essential to assess metropolitan agglomeration economies. First, sub-center formation is a continuous long-term process. Non-center clusters represent an intermediate stage during this process. Second, a total employment threshold (e.g. 10,000 workers) is questionable for three reasons: i) whatever the threshold value is it will be an approximation. Do 9,999 workers form a center?; ii) size and employment distribution in the US metros vary dramatically; applying one single threshold for all is not appropriate; iii) the Census Transportation Planning Package (CTPP) data are known to underestimate employment data.

The major contribution of this study lies in the separation of a metro into five submetro agglomeration units by density and size. The four urban submetro sections in a metro have the following relations: The size of the main-center is larger than each one of the sub-centers. The sub-centers each are larger in size than the non-center clusters. The main-center, sub-centers, and non-center clusters are higher in density than the non-cluster urban areas.

Table 7-1 provides a full framework of the study. The first part of the study measured and compared US metros' spatial structures in 2000 and 2010. The result indicates that metros' macro and micro spatial structure types have been stable. The 10-year timeframe of the study, however, is relatively short considering that metros tend to evolve over longer time scales. The second part of the study explored the influence of spatial structure evolution on regional employment growth rate. The result indicates: (1) gaining sub-center(s) does not significantly decrease regional employment growth rate whereas losing sub-center(s) does, and (2) a sub-center has the most effective density and size to positively influence regional growth rate while larger size (i.e., the main-center) results in lower positive effect, and lower density (i.e., non-cluster urban areas) and smaller size (i.e., non-center clusters) result in negative effect on regional employment growth rate. Therefore, this study provided a more complete analysis of the relationship between spatial structures and agglomeration effects than previous studies.

Table 7-1 Research summary

Objectives	Hypotheses	Important results	
1. Find out whether the majority of the US metros were polycentric in the first decade of the 21st century	a. The majority of US metros were polycentric in 2010.	False	The "2SD" ("10-10") method showed the majority of US metros have been monocentric (coreless) since 2000.
	b. The share of employment outside centers accounted for two-thirds to three-fourths of metro total employment.	True	The employment outside all 361 metros' centers accounted for 71.33 percent and 71.95 percent of US metro total employment in 2000 and 2010, respectively.
			Larger metros → more clusters → less CBD employment share → more non-cluster urban areas employment share
2. Discover patterns of US metropolitan spatial structure evolution	a. The majority of monocentric metros evolved to polycentric from 2000 to 2010.	False	Monocentric and polycentric metros were more stable than coreless metros, with 22 percent of coreless metros, 85 percent of monocentric metros, and 84 percent of polycentric metros remained in their original macro spatial structure types.
			There was no coreless metro evolving to be polycentric and vice versa. A monocentric structure seems to be the intermediate stage evolving from coreless to polycentric.
			Metros evolving from polycentric to monocentric were located mostly in the eastern part of the US.
	b. The majority of metros had their main-center employment share ranking decrease from 2000 to 2010.	False	Only 32 of the 361 metros decreased in main-center employment share rank indicating employment decentralization was not prevalent from 2000 to 2010.
			Metros with low (ranking 2nd and 3rd) main-center employment share were more likely to remain in their macro spatial structure type than metros with high (ranking 4th and 5th) or zero main-center employment share.
			Polycentric metros with higher main-center employment share were more likely to evolve to monocentric, indicating the stronger the main-center, the more likely for the sub-centers to disperse.
			Metros (of all three macro spatial structure types) with lower ranking main-center employment share were more likely to increase in rank and vice versa.
	c. The majority of metros had their number of employment centers remain the same from 2000 to 2010.	True	Most metros (249 out of 361) retained their original (year 2000) number of employment centers.
			Most metros (213 out of 361) retained their original sub-centers employment share.
			Both sub-centers and non-center clusters employment shares were more stable than main-center, non-cluster urban areas, and rural areas employment shares.
			Most employment centers remained in their original locations while others slightly shifted.
3. Assess the influence of spatial structure evolution on regional employment growth rate	a. Monocentric metros remaining monocentric have lower employment growth rate than monocentric metros evolving to be polycentric.	False	Monocentric metros remaining monocentric or evolving to be polycentric have no statistically significant difference in employment growth rates, indicating gaining sub-centers does not significantly increase regional employment growth rate.
	b. Polycentric metros remaining polycentric have higher employment growth rate than polycentric metros evolving to be monocentric.	True	Polycentric metros remaining polycentric have statistically significantly higher employment growth rates than polycentric metros evolving to be monocentric, indicating losing sub-centers decrease regional employment growth rate.
	c. Employment sub-centers will contribute more to employment growth rate than employment non-center clusters do.	True	Initial employment shares in main-center and sub-centers positively affect regional employment growth rate, indicating agglomeration economies exist in high-density large size submetro sections.
	d. Employment non-center clusters will contribute more to employment growth rate than non-cluster urban areas do.	True	Initial employment share in sub-centers has a larger positive effect on regional employment growth rate than that in main-center, indicating larger employment center does not result in higher regional employment growth rate.
			Initial sub-centers employment share and the change in non-center clusters (or non-cluster urban areas) employment share have opposite effect on regional growth rate, indicating the size (or density) of a submetro section may change the direction of influence on regional growth rate.
			Change in non-cluster urban areas employment share has a larger negative effect on regional employment growth rate than that in non-center clusters employment share, indicating lower employment density results in lower regional employment growth rate.

7.2 Study Limitations

This research assumes a metro does not undergo multiple structural changes during the study period. However, this may not hold in reality. This assumption has implications in regards to the claim that the US was never in a polycentric era. For example, if it only takes five years to form an employment sub-center then the metro may have been polycentric during the study period before evolving to be monocentric or coreless in 2010.

This research assumes there is no significant industrial influence on a metro's employment growth rate. This assumption may affect the conclusions on metro structural evolution and employment growth. Industrial composition at the micro level (i.e., the main-center, sub-center, non-center cluster, non-cluster urban and rural) might affect the change in employment share. For example, a finance-based monocentric metro may have a stronger main-center than a manufacturing-based monocentric metro. The finance-based monocentric metro may retain its structure due to the growing finance industry rather than the stability of the monocentric structure. The metros' growing finance industry may also cause regional employment growth rate to increase.

This research does not assess specific changes for any individual submetro section (i.e., main-center, sub-center, non-center cluster, non-cluster urban area, or rural area). Furthermore, submetro sections were assessed using employment share rankings (based on percentages of employment share) rather than absolute employment values. Therefore, even if the rank of the structural indicators remains the same, the following may still change:

i. the location, employment share, and industrial composition of the five submetro sections,
ii. the number of employment centers and non-center clusters, and
iii. the size and industrial composition of each employment center and non-center cluster.

The method to delimit between urban and rural areas causes unequal percentage of rural areas employment across metros--the largest variation is 2 percent. I defined that the census tract polygons with the lowest year 2000 employment density (making up to 2 percent of the total employment) as rural areas. In operation, the 2 percent cutoff may lead to some metros, which may have a very large census tract with low employment density, to have zero rural areas employment if this large census tract makes up more than 2 percent of the total employment. This variation particularly causes inaccuracies in the number of metros in micro spatial structure types. For example, zero employment in rural areas will create additional micro spatial structure types.

7.3 Future Research

One potential area of research is to expand the study period back to the 1970s, controlling for industrial composition. The long-term study period may provide clearer trends and influence of spatial structure on regional economic performance.

A second future research is to investigate how the urban spatial structure of sub-cities (i.e. areas near employment centers) influences their economy, controlling for sub-cities' industrial composition. The current research looking at the average behavior of each submetro section (i.e., main-center, sub-centers, non-center clusters, non-cluster urban areas and rural areas) tends to smooth out individual behaviors of a submetro section (e.g., an employment sub-center). Future studies at the submetro level may include: (1) using a gravity model to measure the dispersion index of sub-cities, (2) plotting the locations of sub-centers or non-center clusters to see if they obey central place theory, (3) tracking the evolution of sub-cities' industrial composition to see if they evolve from specialized to diverse, (4) relating a sub-center's size to its industrial diversity and distance from the main-center to see which factors contribute to permanent sub-centers, and (5) measuring agglomeration economies by the distances among firms, residences, and public spaces.

A third area of potential research is to investigate population (in lieu of employment) distribution characteristics using the same method described in this study. The main objectives would include: (1) evaluating equity in job accessibility for difference groups of residents within a metro, (2) assessing the influence of job accessibility on economic performance, (3) testing to see if the sub-cities' population in a metro obey the rank-size rule (Gabaix, 1999; Brakman et al, 1999).

The last area of potential research is to quantify the influence of urban spatial structure on the economy and the environment. The results may be used to proactively adjust urban spatial structure to benefit both the economy and the environment. Prior to this research, I had focused on the environmental aspects of urban studies and found that the city governments in both the US and China tend to skirt around environmental policies, and instead, dwell on short-term, ostensible, and mostly economic benefits. Moreover, urban spatial structure may present an opportunity to integrate the environmental and the economic considerations by affecting human behaviors directly and indirectly. This area of study would: (1) assess land-use change generated by worker migration to rural areas, (2) search for an effective plan benefiting both the environment and the economy, and (3) thus inform urban planning practice.

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APPENDIX 1

Metros' micro spatial structure types in 2000 and 2010, sorted by name of micro spatial structure types in 2000. The most common micro spatial structure types are in bold: **M41352**, **M40053**, **P43251**, and **M50043**.

CBSA	CBSA_Name	Micro Spatial Structure Types 2000	Micro Spatial Structure Types 2010
25260	Hanford−Corcoran, CA	C00450	**M41352**
36140	Ocean City, NJ	C00453	C00453
48260	Weirton−Steubenville, WV−OH	C00453	C00453
47220	Vineland−Millville−Bridgeton, NJ	C00453	M31452
25980	Hinesville−Fort Stewart, GA	C00453	**M50043**
30300	Lewiston, ID−WA	C00453	**M50043**
41100	St. George, UT	C00453	**M50043**
20940	El Centro, CA	C00543	**M41352**
15260	Brunswick, GA	C00543	**M50043**
23020	Fort Walton Beach−Crestview−Destin, FL	M31452	M31452
40420	Rockford, IL	M31452	M31452
12220	Auburn−Opelika, AL	M31452	**M41352**
29740	Las Cruces, NM	M40050	M50340
11300	Anderson, IN	**M40053**	C00453
15500	Burlington, NC	**M40053**	C00453
11340	Anderson, SC	**M40053**	**M40053**
11500	Anniston−Oxford, AL	**M40053**	**M40053**
12020	Athens−Clarke County, GA	**M40053**	**M40053**
12980	Battle Creek, MI	**M40053**	**M40053**
13020	Bay City, MI	**M40053**	**M40053**
13380	Bellingham, WA	**M40053**	**M40053**
14020	Bloomington, IN	**M40053**	**M40053**
18700	Corvallis, OR	**M40053**	**M40053**
19060	Cumberland, MD−WV	**M40053**	**M40053**
20100	Dover, DE	**M40053**	**M40053**

CBSA	CBSA_Name	Micro Spatial Structure Types 2000	Micro Spatial Structure Types 2010
21820	Fairbanks, AK	**M40053**	**M40053**
22540	Fond du Lac, WI	**M40053**	**M40053**
23580	Gainesville, GA	**M40053**	**M40053**
26620	Huntsville, AL	**M40053**	**M40053**
27620	Jefferson City, MO	**M40053**	**M40053**
28100	Kankakee−Bradley, IL	**M40053**	**M40053**
30340	Lewiston−Auburn, ME	**M40053**	**M40053**
31420	Macon, GA	**M40053**	**M40053**
33780	Monroe, MI	**M40053**	**M40053**
34100	Morristown, TN	**M40053**	**M40053**
36980	Owensboro, KY	**M40053**	**M40053**
39540	Racine, WI	**M40053**	**M40053**
40580	Rocky Mount, NC	**M40053**	**M40053**
40660	Rome, GA	**M40053**	**M40053**
43100	Sheboygan, WI	**M40053**	**M40053**
43340	Shreveport−Bossier City, LA	**M40053**	**M40053**
44940	Sumter, SC	**M40053**	**M40053**
45460	Terre Haute, IN	**M40053**	**M40053**
48140	Wausau, WI	**M40053**	**M40053**
48900	Wilmington, NC	**M40053**	**M40053**
11700	Asheville, NC	**M40053**	M41253
18580	Corpus Christi, TX	**M40053**	M41253
17660	Coeur d'Alene, ID	**M40053**	**M41352**
19260	Danville, VA	**M40053**	**M41352**
24540	Greeley, CO	**M40053**	**M41352**
30620	Lima, OH	**M40053**	**M41352**
30980	Longview, TX	**M40053**	**M41352**
34940	Naples−Marco Island, FL	**M40053**	**M41352**
44100	Springfield, IL	**M40053**	**M41352**
49180	Winston−Salem, NC	**M40053**	**M41352**
16580	Champaign−Urbana, IL	**M40053**	**M50043**
20020	Dothan, AL	**M40053**	**M50043**
24780	Greenville, NC	**M40053**	**M50043**
25620	Hattiesburg, MS	**M40053**	**M50043**
27100	Jackson, MI	**M40053**	**M50043**
27860	Jonesboro, AR	**M40053**	**M50043**

CBSA	CBSA_Name	Micro Spatial Structure Types 2000	Micro Spatial Structure Types 2010
30020	Lawton, OK	**M40053**	**M50043**
41060	St. Cloud, MN	**M40053**	**M50043**
49020	Winchester, VA−WV	**M40053**	**M50043**
39820	Redding, CA	**M40053**	M51342
17900	Columbia, SC	**M40053**	**P43251**
22180	Fayetteville, NC	**M40053**	**P43251**
46940	Vero Beach, FL	M40350	**M40053**
31460	Madera, CA	M40350	M40350
32900	Merced, CA	M40350	M40350
33260	Midland, TX	M40350	M50040
39460	Punta Gorda, FL	M40350	M51243
43900	Spartanburg, SC	M41253	**M40053**
16620	Charleston, WV	M41253	M41253
31540	Madison, WI	M41253	M41253
14500	Boulder, CO	M41253	**M41352**
28940	Knoxville, TN	M41253	**M41352**
43580	Sioux City, IA−NE−SD	M41253	**M50043**
30460	Lexington−Fayette, KY	M41253	P43152
14740	Bremerton−Silverdale, WA	**M41352**	C00354
12100	Atlantic City, NJ	**M41352**	**M40053**
23460	Gadsden, AL	**M41352**	**M40053**
26300	Hot Springs, AR	**M41352**	**M40053**
29180	Lafayette, LA	**M41352**	**M40053**
34620	Muncie, IN	**M41352**	**M40053**
41780	Sandusky, OH	**M41352**	**M40053**
44220	Springfield, OH	**M41352**	**M40053**
44300	State College, PA	**M41352**	**M40053**
12700	Barnstable Town, MA	**M41352**	M41253
15980	Cape Coral−Fort Myers, FL	**M41352**	M41253
34580	Mount Vernon−Anacortes, WA	**M41352**	M41253
35660	Niles−Benton Harbor, MI	**M41352**	M41253
37460	Panama City−Lynn Haven, FL	**M41352**	M41253
10420	Akron, OH	**M41352**	**M41352**
12620	Bangor, ME	**M41352**	**M41352**
13980	Blacksburg−Christiansburg−Radford, VA	**M41352**	**M41352**
15540	Burlington−South Burlington, VT	**M41352**	**M41352**

CBSA	CBSA_Name	Micro Spatial Structure Types 2000	Micro Spatial Structure Types 2010
16300	Cedar Rapids, IA	**M41352**	**M41352**
17020	Chico, CA	**M41352**	**M41352**
17860	Columbia, MO	**M41352**	**M41352**
19340	Davenport−Moline−Rock Island, IA−IL	**M41352**	**M41352**
19460	Decatur, AL	**M41352**	**M41352**
20260	Duluth, MN−WI	**M41352**	**M41352**
21300	Elmira, NY	**M41352**	**M41352**
21500	Erie, PA	**M41352**	**M41352**
21780	Evansville, IN−KY	**M41352**	**M41352**
22500	Florence, SC	**M41352**	**M41352**
24020	Glens Falls, NY	**M41352**	**M41352**
27060	Ithaca, NY	**M41352**	**M41352**
27180	Jackson, TN	**M41352**	**M41352**
27500	Janesville, WI	**M41352**	**M41352**
27740	Johnson City, TN	**M41352**	**M41352**
27780	Johnstown, PA	**M41352**	**M41352**
27900	Joplin, MO	**M41352**	**M41352**
28740	Kingston, NY	**M41352**	**M41352**
29540	Lancaster, PA	**M41352**	**M41352**
30140	Lebanon, PA	**M41352**	**M41352**
31340	Lynchburg, VA	**M41352**	**M41352**
31900	Mansfield, OH	**M41352**	**M41352**
33140	Michigan City−La Porte, IN	**M41352**	**M41352**
33660	Mobile, AL	**M41352**	**M41352**
34900	Napa, CA	**M41352**	**M41352**
37620	Parkersburg−Marietta, WV−OH	**M41352**	**M41352**
37700	Pascagoula, MS	**M41352**	**M41352**
38340	Pittsfield, MA	**M41352**	**M41352**
38860	Portland−South Portland−Biddeford, ME	**M41352**	**M41352**
39140	Prescott, AZ	**M41352**	**M41352**
39340	Provo−Orem, UT	**M41352**	**M41352**
39740	Reading, PA	**M41352**	**M41352**
43300	Sherman−Denison, TX	**M41352**	**M41352**
44060	Spokane, WA	**M41352**	**M41352**
45820	Topeka, KS	**M41352**	**M41352**
46540	Utica−Rome, NY	**M41352**	**M41352**

CBSA	CBSA_Name	Micro Spatial Structure Types 2000	Micro Spatial Structure Types 2010
48540	Wheeling, WV−OH	**M41352**	**M41352**
22520	Florence−Muscle Shoals, AL	**M41352**	**M50043**
47380	Waco, TX	**M41352**	M51243
11540	Appleton, WI	**M41352**	M51342
13460	Bend, OR	**M41352**	M51342
17780	College Station−Bryan, TX	**M41352**	M51342
29340	Lake Charles, LA	**M41352**	M51342
32780	Medford, OR	**M41352**	M51342
39660	Rapid City, SD	**M41352**	M51342
46220	Tuscaloosa, AL	**M41352**	M51342
14260	Boise City−Nampa, ID	**M41352**	P42351
25540	Hartford−West Hartford−East Hartford, CT	**M41352**	P42351
29460	Lakeland, FL	**M41352**	P42351
34820	Myrtle Beach−Conway−North Myrtle Beach, SC	**M41352**	P42351
35980	Norwich−New London, CT	**M41352**	P42351
39100	Poughkeepsie−Newburgh−Middletown, NY	**M41352**	P42351
42020	San Luis Obispo−Paso Robles, CA	**M41352**	P42351
42220	Santa Rosa−Petaluma, CA	**M41352**	P42351
12260	Augusta−Richmond County, GA−SC	**M41352**	P43152
16860	Chattanooga, TN−GA	**M41352**	P43152
21140	Elkhart−Goshen, IN	**M41352**	P43152
23060	Fort Wayne, IN	**M41352**	P43152
25180	Hagerstown−Martinsburg, MD−WV	**M41352**	P43152
29820	Las Vegas−Paradise, NV	**M41352**	P43152
33700	Modesto, CA	**M41352**	P43152
36500	Olympia, WA	**M41352**	P43152
13140	Beaumont−Port Arthur, TX	**M41352**	**P43251**
19380	Dayton, OH	**M41352**	**P43251**
21060	Elizabethtown, KY	**M41352**	**P43251**
25060	Gulfport−Biloxi, MS	**M41352**	**P43251**
27140	Jackson, MS	**M41352**	**P43251**
32580	McAllen−Edinburg−Pharr, TX	**M41352**	**P43251**
22660	Fort Collins−Loveland, CO	**M41352**	P53241
16180	Carson City, NV	M50040	M50040
16220	Casper, WY	M50040	M50040
16940	Cheyenne, WY	M50040	M50040

CBSA	CBSA_Name	Micro Spatial Structure Types 2000	Micro Spatial Structure Types 2010
36220	Odessa, TX	M50040	M50040
47580	Warner Robins, GA	M50040	M50040
18020	Columbus, IN	**M50043**	**M40053**
19500	Decatur, IL	**M50043**	**M40053**
24140	Goldsboro, NC	**M50043**	**M40053**
29020	Kokomo, IN	**M50043**	**M40053**
34740	Muskegon−Norton Shores, MI	**M50043**	**M40053**
36100	Ocala, FL	**M50043**	**M40053**
46660	Valdosta, GA	**M50043**	**M40053**
19140	Dalton, GA	**M50043**	**M41352**
33540	Missoula, MT	**M50043**	M50040
10780	Alexandria, LA	**M50043**	**M50043**
11100	Amarillo, TX	**M50043**	**M50043**
14060	Bloomington−Normal, IL	**M50043**	**M50043**
14540	Bowling Green, KY	**M50043**	**M50043**
16820	Charlottesville, VA	**M50043**	**M50043**
20220	Dubuque, IA	**M50043**	**M50043**
24300	Grand Junction, CO	**M50043**	**M50043**
24500	Great Falls, MT	**M50043**	**M50043**
26820	Idaho Falls, ID	**M50043**	**M50043**
26980	Iowa City, IA	**M50043**	**M50043**
29100	La Crosse, WI−MN	**M50043**	**M50043**
29940	Lawrence, KS	**M50043**	**M50043**
30860	Logan, UT−ID	**M50043**	**M50043**
31020	Longview, WA	**M50043**	**M50043**
34060	Morgantown, WV	**M50043**	**M50043**
38540	Pocatello, ID	**M50043**	**M50043**
39380	Pueblo, CO	**M50043**	**M50043**
42140	Santa Fe, NM	**M50043**	**M50043**
44180	Springfield, MO	**M50043**	**M50043**
41140	St. Joseph, MO−KS	**M50043**	**M50043**
45220	Tallahassee, FL	**M50043**	**M50043**
45500	Texarkana, TX−Texarkana, AR	**M50043**	**M50043**
46340	Tyler, TX	**M50043**	**M50043**
48700	Williamsport, PA	**M50043**	**M50043**
22020	Fargo, ND−MN	**M50043**	M51243

CBSA	CBSA_Name	Micro Spatial Structure Types 2000	Micro Spatial Structure Types 2010
29700	Laredo, TX	**M50043**	M51243
19180	Danville, IL	**M50043**	M51342
22140	Farmington, NM	**M50043**	M51342
22900	Fort Smith, AR−OK	**M50043**	M51342
29140	Lafayette, IN	**M50043**	M51342
43620	Sioux Falls, SD	**M50043**	M51342
28420	Kennewick−Richland−Pasco, WA	**M50043**	P43152
31180	Lubbock, TX	**M50043**	**P43251**
41540	Salisbury, MD	M51243	**M50043**
49700	Yuba City, CA	M51243	**M50043**
24580	Green Bay, WI	M51243	M51243
11260	Anchorage, AK	M51243	M51342
10500	Albany, GA	M51342	**M40053**
17420	Cleveland, TN	M51342	**M40053**
33740	Monroe, LA	M51342	**M40053**
17980	Columbus, GA−AL	M51342	M41253
11020	Altoona, PA	M51342	**M41352**
20740	Eau Claire, WI	M51342	**M41352**
23540	Gainesville, FL	M51342	**M41352**
38220	Pine Bluff, AR	M51342	**M41352**
13740	Billings, MT	M51342	**M50043**
47020	Victoria, TX	M51342	**M50043**
17820	Colorado Springs, CO	M51342	M51243
39900	Reno−Sparks, NV	M51342	M51243
41420	Salem, OR	M51342	M51243
49740	Yuma, AZ	M51342	M51243
10180	Abilene, TX	M51342	M51342
11180	Ames, IA	M51342	M51342
13900	Bismarck, ND	M51342	M51342
22380	Flagstaff, AZ	M51342	M51342
23420	Fresno, CA	M51342	M51342
24220	Grand Forks, ND−MN	M51342	M51342
25500	Harrisonburg, VA	M51342	M51342
41660	San Angelo, TX	M51342	M51342
48300	Wenatchee, WA	M51342	M51342
49420	Yakima, WA	M51342	M51342

CBSA	CBSA_Name	Micro Spatial Structure Types 2000	Micro Spatial Structure Types 2010
10740	Albuquerque, NM	M51342	P43152
48620	Wichita, KS	M51342	**P43251**
12540	Bakersfield, CA	M51342	P52341
21660	Eugene−Springfield, OR	M51342	P53241
37100	Oxnard−Thousand Oaks−Ventura, CA	P24351	P34251
12060	Atlanta−Sandy Springs−Marietta, GA	P34152	P34152
19100	Dallas−Fort Worth−Arlington, TX	P34152	P34152
31100	Los Angeles−Long Beach−Santa Ana, CA	P34152	P34152
33100	Miami−Fort Lauderdale−Miami Beach, FL	P34152	P34152
36260	Ogden−Clearfield, UT	P34152	P34152
42340	Savannah, GA	P34152	P34152
41700	San Antonio, TX	P34152	P34251
46700	Vallejo−Fairfield, CA	P34152	P34251
26420	Houston−Baytown−Sugar Land, TX	P34152	P43152
13780	Binghamton, NY	P34251	**M41352**
45780	Toledo, OH	P34251	P24351
19820	Detroit−Warren−Livonia, MI	P34251	P34152
45300	Tampa−St. Petersburg−Clearwater, FL	P34251	P34152
46140	Tulsa, OK	P34251	P34152
40220	Roanoke, VA	P34251	P34251
47260	Virginia Beach−Norfolk−Newport News, VA−NC	P34251	P34251
36740	Orlando, FL	P34251	P43152
41740	San Diego−Carlsbad−San Marcos, CA	P34251	P43152
20500	Durham, NC	P34251	**P43251**
32820	Memphis, TN−MS−AR	P34251	**P43251**
40140	Riverside−San Bernardino−Ontario, CA	P34251	**P43251**
41180	St. Louis, MO−IL	P34251	**P43251**
16980	Chicago−Naperville−Joliet, IL−IN−WI	P41253	P41253
14460	Boston−Cambridge−Quincy, MA−NH	P41352	P41253
33340	Milwaukee−Waukesha−West Allis, WI	P41352	**P43251**
37340	Palm Bay−Melbourne−Titusville, FL	P42351	M31254
15380	Buffalo−Niagara Falls, NY	P42351	**M41352**
22420	Flint, MI	P42351	**M41352**
25860	Hickory−Lenoir−Morganton, NC	P42351	**M41352**
49340	Worcester, MA	P42351	**M41352**
49660	Youngstown−Warren−Boardman, OH−PA	P42351	P34251

CBSA	CBSA_Name	Micro Spatial Structure Types 2000	Micro Spatial Structure Types 2010
37980	Philadelphia−Camden−Wilmington, PA−NJ−DE−MD	P42351	P41253
38300	Pittsburgh, PA	P42351	P41253
10900	Allentown−Bethlehem−Easton, PA−NJ	P42351	P42351
24860	Greenville, SC	P42351	P42351
40380	Rochester, NY	P42351	P42351
16700	Charleston−North Charleston, SC	P42351	P43152
21340	El Paso, TX	P42351	P43152
31140	Louisville, KY−IN	P42351	P43152
17300	Clarksville, TN−KY	P42351	**P43251**
28140	Kansas City, MO−KS	P42351	**P43251**
35380	New Orleans−Metairie−Kenner, LA	P42351	**P43251**
40340	Rochester, MN	P43152	**M40053**
12940	Baton Rouge, LA	P43152	M41253
17460	Cleveland−Elyria−Mentor, OH	P43152	M41253
28700	Kingsport−Bristol−Bristol, TN−VA	P43152	**M41352**
43780	South Bend−Mishawaka, IN−MI	P43152	**M41352**
48660	Wichita Falls, TX	P43152	P34152
41940	San Jose−Sunnyvale−Santa Clara, CA	P43152	P34251
16740	Charlotte−Gastonia−Concord, NC−SC	P43152	P41352
35620	New York−Northern New Jersey−Long Island, NY−NJ−PA	P43152	P42153
46060	Tucson, AZ	P43152	P42351
12580	Baltimore−Towson, MD	P43152	P43152
22220	Fayetteville−Springdale−Rogers, AR−MO	P43152	P43152
24340	Grand Rapids−Wyoming, MI	P43152	P43152
24660	Greensboro−High Point, NC	P43152	P43152
26380	Houma−Bayou Cane−Thibodaux, LA	P43152	P43152
27340	Jacksonville, NC	P43152	P43152
40980	Saginaw−Saginaw Township North, MI	P43152	P43152
41860	San Francisco−Oakland−Fremont, CA	P43152	P43152
42660	Seattle−Tacoma−Bellevue, WA	P43152	P43152
45940	Trenton−Ewing, NJ	P43152	P43152
47900	Washington−Arlington−Alexandria, DC−VA−MD−WV	P43152	P43152
29620	Lansing−East Lansing, MI	P43152	**P43251**
38900	Portland−Vancouver−Beaverton, OR−WA	P43152	**P43251**
41620	Salt Lake City, UT	**P43251**	**M40053**
45060	Syracuse, NY	**P43251**	M41253

CBSA	CBSA_Name	Micro Spatial Structure Types 2000	Micro Spatial Structure Types 2010
11460	Ann Arbor, MI	**P43251**	**M41352**
17140	Cincinnati−Middletown, OH−KY−IN	**P43251**	**M41352**
19660	Deltona−Daytona Beach−Ormond Beach, FL	**P43251**	**M41352**
28020	Kalamazoo−Portage, MI	**P43251**	**M41352**
30700	Lincoln, NE	**P43251**	**M41352**
44140	Springfield, MA	**P43251**	P32451
26900	Indianapolis, IN	**P43251**	P34251
38060	Phoenix−Mesa−Scottsdale, AZ	**P43251**	P34251
13820	Birmingham−Hoover, AL	**P43251**	P41253
39300	Providence−New Bedford−Fall River, RI−MA	**P43251**	P41352
26180	Honolulu, HI	**P43251**	P42153
35300	New Haven−Milford, CT	**P43251**	P42153
37860	Pensacola−Ferry Pass−Brent, FL	**P43251**	P42153
26100	Holland−Grand Haven, MI	**P43251**	P42351
10580	Albany−Schenectady−Troy, NY	**P43251**	P43152
12420	Austin−Round Rock, TX	**P43251**	P43152
14860	Bridgeport−Stamford−Norwalk, CT	**P43251**	P43152
15180	Brownsville−Harlingen, TX	**P43251**	P43152
19740	Denver−Aurora, CO	**P43251**	P43152
33460	Minneapolis−St. Paul−Bloomington, MN−WI	**P43251**	P43152
37900	Peoria, IL	**P43251**	P43152
42260	Sarasota−Bradenton−Venice, FL	**P43251**	P43152
49620	York−Hanover, PA	**P43251**	P43152
15940	Canton−Massillon, OH	**P43251**	**P43251**
18140	Columbus, OH	**P43251**	**P43251**
19780	Des Moines, IA	**P43251**	**P43251**
25420	Harrisburg−Carlisle, PA	**P43251**	**P43251**
26580	Huntington−Ashland, WV−KY−OH	**P43251**	**P43251**
27260	Jacksonville, FL	**P43251**	**P43251**
28660	Killeen−Temple−Fort Hood, TX	**P43251**	**P43251**
30780	Little Rock−North Little Rock, AR	**P43251**	**P43251**
31700	Manchester−Nashua, NH	**P43251**	**P43251**
33860	Montgomery, AL	**P43251**	**P43251**
34980	Nashville−Davidson−−Murfreesboro, TN	**P43251**	**P43251**
36420	Oklahoma City, OK	**P43251**	**P43251**
36780	Oshkosh−Neenah, WI	**P43251**	**P43251**

CBSA	CBSA_Name	Micro Spatial Structure Types 2000	Micro Spatial Structure Types 2010
38940	Port St. Lucie−Fort Pierce, FL	**P43251**	**P43251**
39580	Raleigh−Cary, NC	**P43251**	**P43251**
40060	Richmond, VA	**P43251**	**P43251**
40900	Sacramento−−Arden−Arcade−−Roseville, CA	**P43251**	**P43251**
41500	Salinas, CA	**P43251**	**P43251**
42060	Santa Barbara−Santa Maria−Goleta, CA	**P43251**	**P43251**
42100	Santa Cruz−Watsonville, CA	**P43251**	**P43251**
42540	Scranton−−Wilkes−Barre, PA	**P43251**	**P43251**
44700	Stockton, CA	**P43251**	**P43251**
47300	Visalia−Porterville, CA	**P43251**	**P43251**
47940	Waterloo−Cedar Falls, IA	**P43251**	**P43251**
36540	Omaha−Council Bluffs, NE−IA	P52341	**M41352**