Polycentricity and the evolution of metropolitan spatial structure

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Abstract

While evidence of polycentric urban form is extensive, questions remain regarding the value of agglomeration economies in an information economy, and hence whether polycentricity will persist over time. This paper examines employment spatial structure in four U.S. metropolitan areas between 1990 and 2009. We describe the spatial distribution of employment among centers and non-center locations across time, examine the persistence of center boundaries, and test for monocentric and polycentric form via density gradient estimations. Results show that the four areas are all polycentric but of different degree. Despite some small fluctuations, metropolitan spatial structure is persistent even in the face of economic shocks in the 2000s: employment centers have not lost their importance and influence in the metro-wide employment distribution over time.

Keywords

Metropolitan (urban) spatial structure, Polycentricity, Employment (sub)centers, Polycentric density function

Introduction

With the rapid population and employment decentralization that took place over the latter half of the 20th century, the standard monocentric urban model developed by Alonso (1964), Muth (1969), and Mills (1972) was called into question. The focus of discussion was agglomeration economies: whether the value of spatial proximity to other firms and labor force persists over time, and if so, at what scale. The existence of employment concentrations within metropolitan areas would suggest sub-metropolitan or localized agglomeration economies. Polycentric urban structure – the presence of multiple employment concentrations – has been identified for many U.S. metropolitan areas, including Los Angeles (e.g., Giuliano and Small, 1991; Giuliano et al., 2007; Redfearn, 2007), San Francisco (Cervero and Wu, 1997), Chicago (McMillen and McDonald, 1998; McMillen, 2001), and Portland (Anderson and Bogart, 2001; Lee, 2007). However, the question remains whether polycentricity is a defining feature of metropolitan areas in the 21st century, or simply a transitional stage in the dispersion process.

In this paper, we examine patterns of employment distribution and the role of employment centers in different metropolitan areas over time. We address two questions. First, is polycentric employment spatial structure a regular feature of urban form? If so, how does the degree of polycentricity vary across metropolitan areas? Second, is the polycentric employment structure persistent over time? Are there any differences in the evolution of employment spatial structure across metropolitan areas?

We use establishment-level time series data to examine employment spatial patterns in four California metropolitan areas: Los Angeles, San Francisco, San Diego, and Sacramento. Our primary data source is the National Establishment Time-Series (NETS) Database for California. We use a minimum density cutoff approach to identify employment centers and compare centers across both time and metropolitan areas. We then use the centers as the starting point for estimating monocentric and polycentric density gradients to test the influence of centers, again across time and metropolitan areas.

The contributions of our study to the literature are as follows. First, based on yearly point-based of 1990-2009, we examine the evolution of metropolitan employment spatial structure over 19 years at the turn of the 21st century. Second, we analyze the persistence of polycentricity not only based on descriptive statistics comparing the employment shares inside and outside employment centers but also based on density gradient estimation to understand the influence of centers on the employment distribution of the entire metropolitan area. We explore the urban form changes within and between the 1990s and the 2000s and their possible relationships with the general economic trends of different periods. Third, we compare the regularities and differences of employment structure changes across four metropolitan areas that represent a broad range of size, geography, and development patterns. Finally, utilizing fine-scale employment data, we devise uniformly shaped and sized spatial units (i.e., one-square-mile hexagons) as the basic units for identifying employment centers; this new approach helps address the methodological problems of defining the contiguity of spatial units found in previous studies and is suitable to capture spatial dynamics of metropolitan evolution over time.

The remainder of this paper is organized as follows. Section 2 presents a brief review of the recent theoretical and empirical literature on employment centers and the evolution of metropolitan employment spatial structure. Section 3 describes the study area, the NETS data, and the methods. Section 4 presents our results. The paper concludes with a summary of findings and implications for future research.

Literature review

Theoretical perspectives

Theories of urban form explain the existence of an employment cluster such as the CBD (Central Business District) based on agglomeration economies and diseconomies in transportation and congestion. Firms benefit from clustering together because of more efficient sharing of inputs, easier access to a large skilled labor pool, and faster and easier knowledge and information exchange with other businesses (Marshall, 1920). As a metropolitan area grows, some firms will seek locations outside the CBD, trading off agglomeration benefits for lower rents and eventually forming subcenters to explore the value of close proximity (Giuliano and Small, 1991; Richardson, 1988).

Will employment centers finally dissolve, leading to a dispersed urban form? Answering this question involves a discussion on the nature and importance of agglomeration economies in a post-industry economy. There are two opposing theoretical perspectives regarding this issue. Some arguments suggest that reduced costs of transportation and communication will allow firms to locate at greater distance from each other; reduced communication costs also supports the emergence of "networked firm" that disintegrate and disperse back-office activities to distant locations (Agarwal et al., 2012; Giuliano et al., 2007). These changes suggest that agglomeration benefits are effective at greater distance and larger geographic scope, such as the regional or national level. The spatial implication of this trend is the dispersion of urban activities.

There are also compelling arguments for the trend towards agglomeration in the “new economy”, especially at the highly localized scale (Duranton and Puga, 2004). Although the development of information and communications technology (ICT) and shift to an information-based economy may lead to the dispersion of back-office activities, high-order activities, such as managerial and executive functions, may concentrate in central locations because access to information “mediators” and expert managers who can access and control information flows become important (Agarwal et al., 2012). Glaeser (2011) suggests that telecommunications and face-to-face interactions are complements rather than substitutes such that improvements in ICT generate more demands for face-to-face interactions and increases the value of knowledge and information learned from people in close proximity.

The growth of consumption activities in cities may also enhance consumer-side agglomeration economies, because different types of complementary consumption activities requiring large volumes of consumers (such as shopping malls and live theaters) to spread fixed costs benefit from clustering together (Glaeser et al., 2001). Urban density also generates demands for specialized products such as designer clothing or 5-star restaurants (Glaeser, 2011). Central place theory suggests that shopping opportunities would cluster in multiple places, following a hierarchical structure, instead of locating in a single center to avoid high congestion costs (Christaller, 1966). Partridge et al. (2010), however, suggest that the effects of production-based and consumer-based agglomeration economies may play different roles in the growth differentials within metropolitan areas: while firms may value the quality of business environment and productivity advantages of central areas within large cities, households prefer consuming leisure activities remote from the urban center, which contributes most to the lower wage gains in the suburban areas of large cities.

Moreover, path dependence may contribute to the continued benefits of localized agglomeration. Garcia-López and Muñiz (2010) find that the benefits of proximity may still accrue to specific places within a metropolitan area that have a history of accessibility advantage. Redfearn (2009) also suggests that the historical advantage of existing employment concentrations can be self-reinforcing if commercial real estate is durable and relatively adaptable to accommodate new employment activities and new functions.

Empirical evidence: Spatial trends of intra-metropolitan employment distribution

Empirical studies on metropolitan spatial structure have employed two ways to address the question of whether polycentricity persists. First, they compare employment shares inside and outside employment centers over time. These studies have found evidence for and against the persistence of polycentricity in multiple metropolitan areas, although different methods of identifying centers limit comparability.

Studies of Los Angeles—part of our study area and the area that gained the most attention in previous studies—have also generated conflicting results. Gordon and Richardson (1996) found that the number and percentage of jobs within employment centers dropped from 1970 to 1990, suggesting a process of spatial dispersion. In contrast, Giuliano et al. (2007) demonstrated that the location of employment centers, their share of total employment, and their characteristics changed very little over a 20-year period (1980–2000), despite rapid growth and major shifts in the local economy. Lee's (2007) study of six US metropolitan areas from 1990 to 2000 (including Los Angeles) also show the results are similar to those of Giuliano et al. (2007); although the degree of polycentricity varies across cities (e.g., the share of employment in the CBD, the share of employment in centers versus outside centers), the structure of cities tends to remain stable over time. The most recent empirical studies available for Los Angeles still documented conflicting results. For example, Giuliano et al. (2019) revealed a persistent polycentric structure in the region, while Kane et al. (2018) found greater variations of employment centers in the region in terms of boundary and industrial composition changes in 1997-2014.

Studies of regions other than Los Angeles also reported mixed evidence on the persistence of polycentricity (Garcia-López and Muñiz, 2010; Kim et al., 2014; Kane et al., 2018). For example, Kim et al. (2014) demonstrated the persistence of polycentricity in Seoul, South Korea, whereas the findings of Garcia-López and Muñiz (2010) suggested the coexistence of polycentricity and dispersion in Barcelona, Spain. While this approach—a comparison of employment shares and growth between employment centers and non-centers over time—is intuitive and easy to interpret, it does not capture the influence of employment centers on the distribution of employment outside employment centers. The results based on this method are also likely to be sensitive to the definition of employment centers, which varies greatly across studies.

The second method reported in the literature to some extent overcomes the limitations of the first approach by testing the influence of centers on the employment distribution of the entire metropolitan area by using the polycentric density function. This approach aligns with the definition of polycentric structure in urban economic theory: locations closer to centers are valued higher by firms, yielding a density function that declines with distance from the center at a decreasing rate (Anas et al., 1998). Changes in the significance and magnitude of center density gradients reveal whether employment location continues to be structured around employment centers or instead becomes more unstructured over time (Garcia-López and Muñiz, 2010).

Small and Song (1994), for example, conducted the benchmark density gradient study using 1970 and 1980 data for the Los Angeles region. The authors showed that density gradients for the CBD decreased in statistical significance while those for the other four subcenters identified for each year increased in statistical significance, implying increased polycentricity over the period. Studies based on other U.S. metropolitan areas and other countries reported similar results. Using the standard polycentric density function, Kim et al. (2014) demonstrated the weakening significance of the CBD in its structuring role but also the growing influence of subcenters on the locations of employment outside centers in Seoul, Korea. Similarly, Sun (2019) found that the urban employment structure in Beijing, China became more polycentric from 2004 to 2013: the estimated density gradients for the two CBDs declined in values and signficance, while those for subcenters increased.

One of the great limitations of previous studies, regardless of their methodology, is their geographic and temporal scope. Most previous literature focused on a single metropolitan area (Giuliano and Small, 1991; Gordon and Richardson, 1996; Small and Song, 1994; McMillen and McDonald, 1998). Findings of earlier studies are difficult to generalize because the data, definition of centers, and estimation methods used differ greatly. Even studies comparing the employment spatial structure of multiple metropolitan areas generally focused on a single point in time, or they were limited in the following aspects.

First, most of these studies compared metropolitan areas that had available data (Lee, 2007) or similar characteristics, such as size (Anderson and Bogart, 2001). These findings provide less systematic insight into how employment spatial structure or its temporal patterns vary by metropolitan areas' characteristics. Second, previous studies examining the temporal changes in the spatial structure of multiple metropolitan areas primarily used descriptive analyses and compared across decades (Yang et al., 2012; Lee, 2007; Arribas-Bel and Sanz-Gracia, 2014). Up until now, we have limited understanding of how the impacts of employment centers on the overall employment distribution within metropolitan areas change over time and how such changes vary across metropolitan areas. Nor do we have much understanding of urban form changes within a decade or at finer temporal scales. Last, but most important, previous studies generally relied on employment data aggregated at the levels of basic administrative units such as TAZs (e.g., McMillen and Smith, 2003) or census tracts (e.g., Yang et al., 2012). Given that the boundaries of TAZs and census tracts change over time, these administrative units may be less suitable for studying the temporal patterns of employment centers. Moreover, census tracts or TAZs are irregular in shape and are in different sizes across locations within a metropolitan area, with these sizes correlated with density. This is especially problematic in areas distant from the city center because the size of the census tract or TAZ is relatively large in such areas. Given that employment density is a key interest of our study, using these spatial units as units of analysis can lead to biased estimates of employment density gradients.

Among previous studies, Kane et al. (2018) is exceptional in that they adopted the one-square km grids, instead of administrative units, to investigate employment concentrations in Los Angeles; the authors documented less stability of employment subcenters compared to the results of tract-level studies. It should be noted, however, that the shape of the grid cells shares important issues with other administrative units in that it is difficult to define the continuity of those spatial units (see the Appendix for further explanations with illustrative examples). Thus, the question of whether polycentricity persists using finer scale establishment-level data deserves to be further explored.

Our study, therefore, is designed to overcome these gaps in the existing literature. The next section introduces our research design and methods.

Research approach, methodology and data

Data, study areas and study periods

We use the National Establishment Time-Series (NETS) database, which is a proprietary dataset developed from Dun and Bradstreet establishment data (Walls and Associates, 2008). Annual data on individual establishments include type of firm, industry sector, number of employees, and geographic location. Our NETS data includes annual establishment-level data from 1990 through 2009 for approximately 5.5 million establishments in California. We choose the four largest metropolitan areas in the state: the Combined Statistical Areas (CSAs) of Los Angeles (LA), San Francisco (SF), and Sacramento (Sac), and the Core Based Statistical Area (CBSA) of San Diego (SD).[1]

These four metropolitan areas provide a wide variety of metropolitan size, economic structure, as well as physical geography. Specifically, the Los Angeles area—the second-largest metropolitan area in the U.S.—contains almost half of California's population (17.6 million in 2005) and jobs (8.7 million in 2005). The Los Angeles area is also known for its polycentric and automobile-oriented spatial structure, whose land area covers about 34,000 square miles, with minimal physical constraints. Entertainment has long been the core industry of the area's economy. Unlike Los Angeles, San Francisco's physical constraints, such as its mountainous terrain and the San Francisco Bay, have contributed to its limited developable areas and high land prices (Saiz, 2010). With 7.3 million persons and 4.2 million jobs (in 2005), San Francisco is the fifth largest CSA in the U.S. Well-known for Silicon Valley and the region's financial hub, the San Francisco area has higher shares of high-tech and financial industry sectors than other metropolitan areas do. The San Diego metropolitan area has 2.3 million residents and 1.6 million jobs in 2005. Along with Los Angeles, San Diego is one of the sunbelt metropolitan areas with historic automobile-oriented development patterns (e.g., low-density residential

[1] We refer to the United States Office of Management and Budget (OMB) for the definition of a CBSA and a CSA. Source: https://www.census.gov/prod/cen2010/doc/sf1.pdf#page=619
The definition of the four metropolitan areas can be found at:
https://www2.census.gov/programs-surveys/metro-micro/geographies/reference-files/2009/historical-delineation-files/list3.xls
The Santa Catalina Island and San Clemente U.S. Military Reservation in Los Angeles County, the Anacapa Island and San Nicolas Island in Ventura County are excluded here.
For San Diego we use CBSA as it has only a single urban core.

areas, wide arterial streets). Most of the infrastructure growth in the Los Angeles and San Diego metropolitan areas occurred during the automobile era (Fulton et al., 2020). Finally, the Sacramento CSA includes the state capital, accompanied by intensive public administration activities and the businesses that support those activities. Compared to other metropolitan areas, it has relatively small population (3.0 million in 2005) and number of jobs (1.1 million in 2005). Similar to Los Angeles, Sacramento is built on a vast basin with minimal physical constraints. Namely, the four metropolitan areas cover a fairly wide variety of metropolitan characteristics so that they can be deemed a suitable set for our study.[2]

We conduct comparisons across metropolitan areas and across time in order to better understand the structure and dynamics of employment centers. To find the appropriate time interval, we conduct a series of two-sample Kolmogorov-Smirnov tests (K-S tests) to explore whether the probability distributions of employment across spatial units within each metropolitan area between any two consecutive years are significantly different from each other.[3] Based on K-S results for all metropolitan areas, employment distribution by hexagons between 1990 and year 2009 are likely to fall into 5 categories (approximately five years). As a result, we selected 1990, 1995, 2000, 2005, and 2009 as representative years of each category for temporal comparisons. Here, a spatial unit refers to the one-square-mile regular hexagon.

Basic trends in employment and population growth are summarized in Table 1. Over the 1990-2005 period all four regions experienced positive employment growth, but the effects of the "Dot-Com" boom and recession of 2001 is evident for San Francisco. Population growth parallels employment growth for Los Angeles and San Diego from 1990 to 2005, but was slower than employment growth in San Francisco and Sacramento. Given that the labor force participation rate declined in San Francisco during the decade, and was stable in the other metropolitan areas, these differences are not explained by the labor force participation rate.[4] The trends in the two regions may reflect increased commuting from

[2] Given that we focus only on metropolitan areas in California, state-level geo-political and socio-economic characteristics, which could influence metropolitan spatial structure, may be sufficiently controlled.

[3] Here the null hypothesis of the K-S tests is that employment distributions across spatial units between any two years in an area are drawn from the same distribution function.

[4] The civilian labor force participation rates in the two component CBSAs of the San Francisco Metropolitan area, the San Francisco-Oakland-Fremont and the San Jose-Sunnyvale-Santa Clara, decreased from 73.5% to 63.8%

outlying areas not captured in the study boundaries.

Methods for identifying employment centers

Employment centers are defined as areas with concentration of employment large enough to exert a potential influence on the metro-wide employment and population distributions (Giuliano and Small, 1991, Anas et al., 1998, McMillen, 2001). Three types of methods for identifying employment centers have been developed in previous studies (see Agarwal et al., 2012 for reviews): (1) methods based on minimum size and density (Giuliano and Small, 1991); (2) estimation of density gradients to identify potential centers (McDonald, 1987); and (3) various two-step methods using locally weighted regression (LWR) to smooth the density surface and then identify centers (McMillen, 2001; Redfearn, 2007). Each approach has advantages and disadvantages. In all cases, they involve some type of arbitrary decisions, such as a minimum job density criterion (method 1), or the criterion for what constitutes a sufficient difference in the smoothed density surface (method 3).

Given that there is no generally agreed upon method for identifying employment centers, here we follow the Giuliano and Small (1991) method, which is the most widely used. Employment centers are defined as a set of continuous zones having a given minimum employment density and together having a given minimum total employment size. Using the minimum size/density cutoffs to predefine employment centers, instead of identifying centers endogenously from an estimated density surface that is based directly on a monocentric model, allows us to conduct hypothesis tests for monocentricity. Again, we use a one-square-mile regular hexagons as the geographic unit to identify employment centers. As all pairs of hexagons share a boundary, the boundaries of each employment centers can be directly identified by aggregating a cluster of hexagons meeting the density cutoff and sharing at least one boundary with each other (see the Appendix for details). Compared with administrative units (e.g. census tracts or fishnet grids), hexagons may be more suitable spatial units for exploring the stability or instability of employment subcenters over time. We demonstrate this point by comparing our findings with those of Kane et al. (2018) in the Results section below.

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and from 70% to 69.6%, respectively, between 1997 and 2005. Source:
http://www.bls.gov/opub/gp/laugp.htm
http://www.bls.gov/opub/gp/pdf/gp97_complete.pdf
http://www.bls.gov/opub/gp/pdf/gp05full.pdf

One of the major criticisms of the cutoff method is that the choices of thresholds for employment density and total employment rely on local knowledge, which would affect the total number of centers identified (McMillen, 2001). To limit the influence of local contexts, we identified the cutoff based on the statistical distribution of employment density. For example, Pan (2003) pointed out that with normal distribution assumption, the minimum density cutoff of 10 jobs per acre is approximately two standard deviations from the mean density (or the 95th percentile value), while the cutoff of 20 jobs per acre is approximately three standard deviations from the mean (or the 99th percentile value) in Los Angeles, CA, when census tract level data were used. However, our K-S tests show that employment density (by hexagonal cells) does not follow a normal distribution, either in raw or natural log form. We therefore use the 95th and 99th percentile value of employment density rather than standard deviation units as the reasonable lower and upper limits for density cutoffs.

As the cutoffs for total employment, we retain the Giuliano and Small (1991) criteria of 10,000 and 20,000 as the lower and upper limits for total employment. These numbers are considered as reasonable because a cluster of, for example, 10,000 total employment amounts to a "company town", which would produce sizable influence on nearby employment within a metropolitan area (McMillen, 2003). Thus, we identify two types of centers: "95%/10K" (95^{th} percentile density and minimum 10,000 jobs), and "99%/20K" (99^{th} percentile density and minimum 20,000 jobs).

Methods for analyzing boundary change of employment centers

Following the work of Kane et al. (2018), we use the persistence scores to identify whether and to what extent the boundaries of each center changed over time. Using the boundaries of centers identified in 2000 as a reference, the boundary persistence of center i for each of the other study years (i.e., 1990, 1995, 2005, 2009) are represented as:

$$Persist_{i,year} = \frac{Center_{i,year} \cap Center_{i,2000}}{Center_{i,year} \cup Center_{i,2000}} \qquad (1)$$

where the nominator is the number of hexagons identified as components of center i in both 2000 and any one of the other 4 years and the denominator is the total number of composite hexagons of center i at either year.

Methods for verifying polycentric structure of employment distribution

The polycentric model extends from the monocentric model and assumes that employment distribution is determined by both access to the CBD and to other subcenters. The form of the polycentric density function depends on assumptions about how the centers influence employment distribution. There are three possibilities (Heikkila et al., 1989; Small and Song, 1994): 1) if employment centers are perfect substitutes, the polycentric function would be the "upper envelope" of functions for every center (equation 2); 2) if employment centers function as complements to each other, the polycentric density function would be the product of functions for every center (equation 3); 3) if the influence of employment centers is between the two extremes, the polycentric density function would be the sum of functions for every center (equation 4). Using the negative exponential functional form, the three polycentric models are illustrated as follows (Anas et al., 1998):

$$\mathrm{Den}_i = \mathrm{Max}_j[\mathrm{A}_j \exp(-\beta_j Dist_{ij})] \qquad (2)$$

$$\mathrm{Den}_i = \mathrm{A} \prod_j^J [\exp(-\beta_j Dist_{ij})] \qquad (3)$$

$$\mathrm{Den}_i = \sum_j^J [\mathrm{A}_j \exp(-\beta_j Dist_{ij})] \qquad (4)$$

where Den_i is the density at location i, $Dist_{ij}$ is distance from location i to employment center j, A_j and A are intercepts, and β_j is the density gradient.

In this study, we use the multiplicative form (equation 3) to estimate the influence of employment centers on employment density distribution. The advantage of using this specification is that it can be transformed into a linear exponential form that can be easily estimated by linear regression techniques such as OLS. This avoids the convergence problems and high computational costs of the nonlinear least squares (NLS) method as required for the estimation of the additive function (equation 4). The disadvantage of using the multiplicative form, however, is that the assumption on the relationships between centers is less realistic than that for the additive form (Small and Song, 1994). The intercept terms for functions of all centers are also forced to be the same in this specification. This might cause biased estimates of polycentric density gradients. But given that our main purpose is to verify the existence of polycentricity and explore its persistence over time, not to compare density gradients of different employment centers within a metropolitan area, these biases should not affect results. The same type of biases for the estimated density gradients for the same set of employment centers will exist over time.

We use a linear exponential form of polycentric density function, which derives from the multiplicative function by taking natural logs on both sides of equation 2:

$$\ln \mathrm{Den}_i = \alpha_0 + \beta_1 Dist_{iCBD} + \sum_j^J \beta_j Dist_{ij}^{-1}\,,\;\; j \neq 1 \qquad (5)$$

where Den_i refers to the density at location i that is outside of employment centers, $Dist_{iCBD}$ is distance between location i and the CBD, $Dist_{ij}$ is distance between location i and employment subcenter j, β_1 is the density gradient for the CBD, β_j is a parameter referring to the density gradient of subcenter j. An inverse distance function for subcenters is used to avoid the multicollinearity problem caused by the high correlation between the distances to other centers in proximity (Heikkila et al., 1989; McDonald and Prather, 1994). This specification also assumes that while the effects of the CBD extend to the whole metropolitan area, the effects of other employment centers are limited to a relatively short distance (McDonald and Prather, 1994).[5] In equation (5), the density gradient for subcenter j at a specific distance (d) from the subcenter is calculated as $-\frac{\beta_j}{d^2}$. The larger the value of coefficients for the inverse of distance, the steeper the density gradient.

Another question is the choice between the "95%/10K" centers and the "99%/20K" centers. Theoretically, the more centers that are incorporated in the polycentric model, the closer the estimated density surface will be to the actual one. However, increasing the number of centers increases the correlation in distances from one center to the others, and hence generates a greater multicollinearity problem. Thus, we use the "99%/20K" centers in the density gradient estimations.

Results

We examine changes in the basic charateristics of employment centers, their share of total

[5] This assumption is supported by empirical evidence. First, the CBD has the longest mean commute time and largest share of long commutes, while other smaller subcenters have more localized commute sheds (Cervero and Wu, 1997; Shearmur and Motte, 2008). Second, suburban firms rely mostly on financial, business, and professional service providers located in the central city, implying the metro-wide influence of the CBD in terms of high-level economic functions (Schwartz, 1992a; 1992b).

employment, and their capacity to influence the overall employment distribution to reveal spatial trends of employment within the four study regions.

Descriptive analysis: Employment spatial structure (and trends) within the four metropolitan areas

Table 2 gives the 95th and 99th percentile employment densities, the number of the two types of centers, and some other characteristics of the 99%/20K centers identified for each area in the five years. As expected, the minimum employment density cutoffs vary across metropolitan areas, which reflect their differences in geographic size and overall development density. The minimum density cutoff values are highest for Los Angeles, followed by San Francisco, while those for San Diego and for Sacramento are about 2/3-3/4 and 1/4-1/3 of the value for Los Angeles, respectively. The density cutoff values are relatively stable, with a general upward trend particularly in 1990–2000, reflecting more job growth during this period. The density cutoff for the period of 2005-2009 exhibits declines due to the Great Recession and financial collapse in 2008.

Table 2 also shows that the number of employment centers is related to metropolitan size: Los Angeles has the greatest number of centers, followed by San Francisco. San Diego and Sacramento have many fewer centers. Comparing among the 99%/20K centers, we find that centers in San Francisco are on average larger and denser and their share of total employment is larger than those in Los Angeles. Despite the difference in the number of centers, Los Angeles is comparable to San Diego in terms of the average employment density of (the 99%/20K) centers and the percentage of employment within centers. In San Francisco and Sacramento, a much larger share of employment is inside centers.

Maps of the 2000 centers for each metropolitan area are shown in Figure 1. The 99%/20K centers are numbered by rank size. We also show the 95%/10K centers. It can be seen that in all cases the 99%/20K centers are subsets of the 95%/10K centers that have the highest density.

We also compare the distribution of employment across the CBD, the second largest center and other centers (see Figure 2). Compared with the CBD in Los Angeles and San Diego, the CBDs in San Francisco and Sacramento account for a much larger share of all employment in centers. Sacramento is the most centralized, with almost all center employment located in the CBD; San Diego is least so. Although Los Angeles and San Francisco are identified as typical polycentric regions with a relatively large number of centers, San Francisco is more "centralized" than Los Angeles given that the employment share of its two largest centers is larger.

We now turn to temporal comparisons. Table 2 shows that the number of centers remained stable in San Diego and Sacramento, whereas it overall shows an increasing trend in Los Angeles (except for the great recession period) and in San Francisco (except for 1995). Generally, in all metropolitan areas, there were temporal variations in total employment, the average number of jobs per center, and average job density in centers, likely reflecting the general economic trends. For example, employment centers in San Francisco on average experienced significant reduction in size and density in 2000-2009, possibly due to the effects of the "Dot-Com" boom and recession of 2001 and financial collapse in 2008. However, despite the varying number of centers and total employment in centers over time, the share of employment within centers does not change significantly in any metropolitan areas; this implies that the absolute and relative importance of employment centers to the metro-wide employment distribution is persistent over time. For example, in Los Angeles and San Francisco, the percentages of employment within centers ranged between approximately 15% to 17% and 22% to 25%, respectively, over the 19-year period.

Figure 2 also gives comparisons of employment shares in CBD and other employment subcenters over the study period (using the "99%/20K" cutoffs). Again, we can visually confirm that, overall, the share of total employment within employment centers remains relatively stable across years in all metropolitan areas. However, Figure 2 reveals some variations in the relative shares of employment across centers over time. Specifically, the CBD's share of total employment gradually declined in Los Angeles and San Francisco from 1990 to 2009, but the yearly changes are small. The Sacramento CBD significantly increased its share of total employment between 1995 and 2000 only because it expanded and merged with the second largest 1990/1995 center. The employment share of the second largest center remained stable in Los Angeles and San Diego over the two decades. It declined significantly in San Francisco between 2000 and 2005 because its second largest center (San Jose Downtown) "split" into two smaller centers (North San Jose and North Santa Clara) in 2005. In Sacramento, the employment growth in Rancho Cordova make it become the third largest center in 1995 and the second largest center since 2000 after the expansion of the CBD, while the share of employment in the new second largest center is lower compared with the previous location.

Finally, relative locations and boundaries of centers are in general stable over time. Although the configuration of centers within a metropolitan area changes over time, some places always maintain the status of center-locations, even if the shape of centers identified in different years changes.[6] Table 2 shows that except Sacramento in the early 1990s, the average persistence scores calculated for all centers in the 4 regions identified using either the “95%/10K” or “99%/20K” cutoffs are always more than 0.5. In other words, regardless of the criteria used for identifying the centers, more than half of the composite hexagons of the centers identified in Sacramento since 1995 and in the other 3 regions throughout the study period maintained their centers’ status. For Los Angeles, San Francisco, and Sacramento, the average persistence scores for “95%/10K” centers in 1995-2009 period are more than 0.7, while for San Diego the average persistence scores are no less than 0.69 for “95%/10K” centers in 2000-2009 period and for “99%/20K” centers in 1995-2009 period. For Los Angeles and San Francisco where the number of “99%/20K” centers fluctuated during the study period, all the newly emerged “99%/20K” centers in 1995-2009 were part of the 95%/10K centers identified in 1990, while all the hexagons losing status of “99%/20K” centers in any of the four years maintain their membership of “95%/10K” centers in the same year. For example, the two “99%/20K” centers (North San Jose and North Santa Clara) for San Francisco identified in 2005 that were “collapsed” from the second largest “99%/20K” center (San Jose Downtown) identified in 2000 still belong to the same “95%/10K” center in 2005; the total land areas of the two “99%/20K” centers still cover more than 57.1% of the original San Jose Downtown center identified in 2000.

There is no clear relationship between the persistence of centers’ boundaries and the general economic trends or the general scale of metropolitan areas. Using the “99%/20K” centers as examples, we observe that during the 2000-2005 period with the dot-com bubble, the coverage area of centers changed most for San Francisco, followed by Sacramento and Los Angeles, while the boundaries of centers for San Diego were not affected; during the 2005-2009 period with the great recession, the average persistence scores of centers decreased in Los Angeles and San Diego, but increased in San Francisco and Sacramento.

Compared with Kane et al.’s (2018) study, the persistence scores of centers found in this study using the one-square mile hexagons (about 2.59-square km) are in general larger than the 0.43 value

[6] The maps of 1990, 1995, 2005 and 2009 centers for the four areas are not shown here, but are available upon request.

using one-square km grid cells and fairly comparable to the 0.62 value using 4-square km grid cells and the 0.5 value using census tracts (e.g., 6.5 square km according to Lin et al. (2020)) in Los Angeles. Furthermore, some of the centers found to have fluctuating boundaries in Kane et al's (2021) study are found to have relatively stable boundaries in this study. For example, the Burbank (Hollywood studios, Center 10 in 2000) have persistent boundaries throughout the 19-year period, while the John Wayne Airport (Center 2 in 2000) has more than 70% of the land coverages unchanged during the study period. Another center Torrance (Center 15 in 2000) also found to have unstable boundaries in Kane et al.'s study (2018) is found to have consistent boundaries during the 1995-2005 period and only disappears during the 2005-2009 period, but its composite hexagon still maintains its membership of a "95%/10K" center in 2009. That is, our study shows greater stability of employment centers than the previous longitudinal study and provides more support for the path dependence argument of urban form evolution—changes in the location of economic activity are gradual and incremental given a relatively fixed built environment. In addition to differences in the geographic scales of analysis units, it is likely that the use of hexagons instead of grid cells makes the identification of centers' boundaries unambiguous and less vulnerable to the small changes in the employment locations.

Regression analysis: The impacts of employment centers

We use a multiplicative functional form (equation 5) to estimate the polycentric density function for each area. Distance to the 99%/20K centers from each non-center hexagon is calculated as Euclidean distance to the peak-density hexagon of each center. The inverse of distance variables is still highly correlated in Los Angeles and San Francisco because some centers are located very close to one another. Thus, each center may not exert an independent influence on the employment distribution. To reduce the multicollinearity problem, we follow Small and Song (1994) and omit the smaller of any two centers (as of 1990) which are within the service boundary of each other. We use the 5th percentile value of distances between pairs of employment centers as the minimum service boundary of centers for each region. As can be seen in Figures 1(a) and 1(b), in most cases, these co-located 99%/20K centers are part of the same 95%/10K center.

Testing for polycentricity.

We first test the (null) hypothesis that each metropolitan area is monocentric. We estimate monocentric and polycentric models using the 1990 data, and use the F test to determine whether the added distance variables in the polycentric model are significant. The results are consistent across all four metropolitan areas: the null hypothesis is rejected in every case. The additional center variable coefficients are significant and of the expected sign. To further test whether there exists a significant difference in the estimated coefficients for the CBD between the monocentric model and the polycentric model, we perform Wald tests to compare difference between the two coefficients (Judge et al. 1985). Table 3 (bottom row) shows that the value of Chi2 statistic is significant at $p<0.01$ level for the results of all areas. Thus, adding the other center variables significantly decreases the magnitude of the CBD distance coefficient, and increases the explanatory power of the model. These results imply that the coefficients of distance to CBD in the monocentric model are really the "combined effects" of distance to employment centers. Together, the results in Table 3 provide strong evidence for polycentricity in 1990.

We also estimate monocentric and polycentric density functions for employment in 2009 with the 2009 centers, keeping all the "center locations" that are used in the estimation of employment density for 1990 and retained their centers' status in 2009. Similar to the results in Table 3, the F test and Wald test in Table 4 indicate that the monocentric model is rejected in every case and most of subcenters play significant roles in structuring the overall employment patterns in 2009.

Our results also reveal that the degree of polycentricity varies across the four regions. First, the differences in the goodness-of-fit across the polycentric models imply that employment centers within Los Angeles or San Diego as a group exert greater influence on the location of the overall employment than they do in San Francisco and Sacramento, even though the share of employment within centers is lower in Los Angeles and San Diego. Second, the estimated coefficients of distance to CBD in the polycentric models vary across the four metropolitan areas. The density gradients for the Los Angeles CBD and the Sacramento CBD are relatively flat, around 0.01, while the density gradient for the San Diego CBD is much steeper (around 0.08-0.09). These results imply that the influence of CBDs in Los Angeles and Sacramento is more extensive within the two regions, while the influence of the San Diego CBD is more localized.

Finally, it might be argued that the 99%/20K criterion may be too high for San Diego and Sacramento, given their much smaller overall size (population and employment). We, therefore, ran the same polycentricity tests for these metropolitan areas using the 95%/10K centers. In both cases, the CBD gradients are slightly flatter, polycentricity is confirmed, and the overall goodness-of-fit is only slightly better. Given that these results do not change our conclusions, we do not report them here.

The persistence of polycentricity

Our second question is whether employment centers maintain their influence on the employment spatial structure over time. To address this question, we chose the centers identified in 2000 (the middle year of the study period) as a basis of this analysis because there were some variations in the number and locations of identified centers across years. As shown in Figure 2, the growth patterns of most 2000 centers are quite similar to the general employment growth pattern in the four regions: the employment size of most centers increased during the first decade (1990-2000) when there was a general upward trend in economic growth but decreased during the 2000-2009 period when the “Dot-Com” bubble (in 2001) and the Great Recession (between 2007 and 2009) occurred. The CBD of Los Angeles is the only center that exhibited negative growth in both 1990-2000 and 2000-2009 periods, while West Los Angeles (Center 4) and Burbank (Hollywood studios, Center 10) in Los Angeles are the only two centers that experienced positive employment growth throughout the 19 years (see Figure 2).

Next, we estimate the polycentric employment density functions for each region in 1990, 1995, 2000, 2005, and 2009 with respect to the 2000 centers. Based on these estimation results, we compare below the adjusted R-square of the polycentric models and examine the changes in significance and magnitude of the estimated density gradients across five years. We also explore whether and how these changes are related to the growth patterns of the centers and the general economic trends.

Tables 5-8 present the results for each year and metropolitan area. We observe that the goodness-of-fit of the polycentric density functions for all the five study years are almost invariant within each region. These results suggest that the difference in the degree of polycentricity remains similar over time. We also observe that all the employment centers in the four metropolitan areas, except for the Santa Monica center in Los Angeles, are found to have a significant influence on the overall employment structure with expected signs, regardless of the study year.

To test the stability of center gradients, we perform Wald tests for the coefficients for each center estimated between 1990 and 2009 and those between four pairs of neighboring study periods (i.e., 1990 vs. 1995; 1995 vs. 2000, 2000 vs. 2005, 2005 vs. 2009); the results of the Wald tests are also reported on the right side of Tables 5-8. We find that the magnitude of the coefficients for CBD remains stable over the study period in San Francisco and San Diego (at $p<0.05$ level), but it shows some short-term fluctuations in the other two regions. In Los Angeles, the CBD's density gradients increased between 1990 and 2009; however, not only a significant increase in the Los Angles CBD's density gradient mainly occurred between 1995 and 2000, but the magnitude of such increase was also small (0.001 jobs per acre). In Sacramento, the estimated density gradients of CBD decreased significantly between 1990 and 1995 by 0.004 jobs per acre but increased between 2000 and 2009 by 0.006 jobs per acre. As a result, we find no significant changes in Sacramento CBD's density gradients between 1990 and 2009. Given that the changes in the estimated coefficients for CBD are either insignificant or very small in all areas, we conclude that the CBDs mostly maintained their influence on the overall employment pattern in each area, despite the decentralization trends during our study period.

Tables 5-8 also indicate the results of Wald tests for subcenters in each area. Given that the inverse distance between each subcenter and hexagons was employed for centers other than CBD, coefficients on other subcenters exhibit positive signs. Notably, the magnitude of these coefficients varies greatly across centers, suggesting their different influences on the metropolitan employment structure. Comparing across different periods, we observe that most of subcenters in the two larger regions exert significant and non-varying influence on metro-wide employment distribution for all five study years, but the influences of a few subcenters do have some small fluctuations. In Los Angeles, the estimated coefficients for five 2000 subcenters changed significantly during the 19-year period (see Table 5): John-Wayne Airport (Center 2), LAX (Center 4), Pasadena (Center 8), Long Beach downtown (Center 14), and Commerce (Center 16). In San Francisco, three centers – San Jose downtown (Center 2), West Oakland (Center 3), and Walnut Creek (Center 9) – have their estimated coefficients changed significantly across years (see Table 6). However, the degree of such changes is still not that large. For example, comparing the results of 1990 and 2009, the density gradient for the John-Wayne Airport center in Los Angeles becomes steeper by only about 0.007 jobs per acre at the distance of 10 miles from the center. For the San Jose downtown center in San Francisco, the increases in the density gradients between 1995 and 2000 at the 10-mile distance of the center is about 0.002 jobs per acre, while the decreases in the density gradients between 2000 and 2005 at the same distance is about 0.003

jobs per acre.

The variations in the influences of some subcenters are also found in the other two smaller metropolitan areas. The second largest center of San Diego—Eastern San Diego—experienced a decrease in the estimated density gradient at the 10-mile distance (i.e., about 0.01 jobs per acre from 1990 to 2009). The estimated coefficients for the only 99%/20K subcenter in Sacramento, Rancho Cordova, also increased by a similar magnitude between 1990 and 2009 (i.e. around 0.009 jobs per acre at the 10-mile distance of the center); however, we also find that the changes in the estimated coefficients between pairs of neighboring study years are incremental and insignificant.

The direction of changes in the influence of subcenters over time is also noteworthy; out of the 10 employment subcenters in the four regions experiencing significant changes in their influence on the overall employment structure, only 4 subcenters show a consistently decreasing trend in coefficient magnitude over the entire study period; the rest of the subcenters show either fluctuating or increasing trend in coefficient magnitude over time. Therefore, although the estimated impacts of some employment subcenters on the overall employment locations in the four regions changed over the study period, we confirm that the magnitude of such changes is relatively small, and the directions of changes are inconsistent across centers.

Some might wonder what explains the temporal variations in the influence of some subcenters. For those centers with changing effects on the metropolitan employment structure over time, we do not observe any consistent relationship between the direction of such changes and the growth patterns of the corresponding centers. For example, both the San Jose downtown center and the Walnut Creek center in San Francisco experienced negative employment growth between 2000 and 2005, but the estimated density gradient decreased for San Jose and increased for Walnut Creek during this period. In Los Angles, both the Pasadena center and Commerce center showed a decrease in density gradients between 1995 and 2000, though these centers experienced employment growth during this period.

The relationship between changes in the impacts of these few centers and the general economic trends seems to be unclear, either. In other words, increased density gradients for employment centers are not always observed for the periods of 1990-1995 or 1995-2000 when the general economy enjoyed stable growth, while decreased density gradients for employment centers are not always observed for the periods of 2000-2005 or 2005-2009 with the downward economic trends. Thus, the links between the general economic upturn/downturn and the role of employment centers in the overall urban spatial structure are not clear here and may deserve to be further explored in the future. However, for all the four metropolitan areas, our results provide no evidence that polycentricity is gradually giving way to dispersion regardless of the general economic trends. Moreover, we observe that the goodness-of-fit of the polycentric density functions for the five years are almost invariant within each metropolitan area. Therefore, there is no evidence that these metropolitan areas are becoming more or less polycentric during the two decades.

Conclusions

Our results provide substantial support for polycentric urban form. Employment centers are identified in all four metropolitan areas, and using a highly restrictive center definition, they account for approximately 10 to 26% of total employment within each region. Employment distribution is better explained by the polycentric model than the monocentric model for all metropolitan areas and time periods. The CBD continues to exert significant but weaker influence when other centers are included.

However, we also find that the degree of polycentricity varies considerably. First, Los Angeles and San Francisco have many more centers than San Diego and Sacramento; we surmise that the number of centers is related to metropolitan size, which also aligns with Hajrasouliha and Hamidi's (2017) findings. Second, the total share of employment in centers varies. Los Angeles and San Diego on average have smaller shares than San Francisco and Sacramento. The CBDs of Los Angeles and San Diego also account for a smaller share of center employment. The overall fit of the polycentric density functions for Los Angeles and San Diego are very similar and are always higher than that for San Francisco. These differences suggest that San Francisco is relatively more centralized than Los Angeles; more employment is located within centers, and more employment is concentrated in the largest centers. Third, Sacramento is the weakest case for polycentricity; the polycentric model for Sacramento is based on a large CBD and one much smaller center. Although centers account for about 25% of all employment in Sacramento from 1995 and on, they are less important in explaining the overall employment distribution for the region. That is, Sacramento may be described as closer to monocentric and dispersed.

These findings suggest that, along with metropolitan size, geography and development patterns might play important roles in explaining the degree of polycentricity. The absence of geographical constraints allows for less polycentric but dispersed development in Sacramento. In contrast, the physical constraints of the bay and mountains may help to explain the relative concentration of employment in centers in San Francisco. It is also possible that the economic structure of San Francisco—higher shares of high-tech and financial industry sectors—further contributes to its more centralized patterns, given that these industry sectors value agglomeration more than other sectors do (Angel, 1991; Kolko, 2010). The automobile-oriented development patterns of Los Angeles and San Diego also likely explain similarities in their smaller shares of employment in the CBDs and larger centers. Along with its high traffic congestion levels, Los Angeles's greater share of the entertainment industry might further promote its polycentric structure, as this sector also values cheaper land prices due to its needs for larger space (e.g., production studios and movie sets).

Differences in spatial structure across metropolitan areas are also overall persistent over time. Although the number of employment centers and the average job density and total employment in such centers vary across years, the relative importance of employment centers to total employment, as well as the relative dominance of the CBD are unaffected by the general economic trends. According to Partridge et al. (2010), the continued growth gap between central and suburban areas within large metropolitan areas (i.e., population larger than 1.5 million) is mostly driven by household preferences for amenities of suburban areas (e.g., less air pollution and traffic congestion) and less so by increasing productivity disadvantage of suburban areas relative to their corresponding central areas (possibly due to the prominence of high-order activities in central areas). Employment concentrations are also stable over time, despite the existence of economic shocks in the 2000s. All of the new 99%/20K centers were located within existing 95%/10K employment clusters. The boundaries of employment centers are also found to be relatively stable over time; except for Sacramento in the early 1990s, more than 50% of employment centers' land coverage in the four regions remain unchanged during the period.

Finally, our results suggest that polycentric urban form is relatively persistent for all metropolitan areas studied. For most of employment centers in the study area, their influences on the overall urban spatial structure remain stable over time. Though the estimated impacts of some employment subcenters on the overall employment locations changed during the 19-year period, the magnitude of the changes in the impacts is relatively small. There is no consistent evidence that the direction or the magnitude of changes in the effects of employment centers are related with the general economic trends or the employment centers' own growth or decline. These results again echo Partridge et al.'s (2010) findings that growth patterns at the sub-metropolitan level are more related with agglomeration economies than with general economic shocks. The continued existence and influence of employment concentrations in the four regions of unique forms suggest that the forces of agglomeration continue to be strong. Multiple employment centers provide local agglomeration economies at varying scales, from the CBD to smaller centers. Given that different industry segments value agglomeration differently, polycentricity provides the flexibility of multiple location opportunities. Multiple degrees of local agglomeration economies also fit with changing industry structure; as technology and preferences continue to evolve, polycentricity allows for adaptation of the built environment to these changes. With the polycentric urban form, the positive benefits of agglomeration (productivity enhancement via scale economies, diverse and specialized labor pool accessibility, supplier accessibility, and transportation and communication infrastructure) are achieved, while negative externalities, such as high land costs, wage, and congestion, are reduced (Giuliano et al., 2019; Partridge et al., 2010). The variety of polycentric urban forms we have observed also supports the path dependence argument. As suggested by Redfearn (2009), "employment centers can constantly be remade" in the same places, which have gained advantages over time by accumulation of network infrastructure and real estate development. New types of economic activities can be continually accommodated by modifying existing commercial and industrial real estate structures. The particular form of these centers is the result of both geography and history.

Although the 19-year period our study spanned is only a short period of time relative to the longevity of the built environment, our results are consistent with previous studies: polycentricity appears in many metropolitan areas, and it persists over time. Ideally one could examine metropolitan areas over much longer periods of time; to date the lack of comparable employment data has prevented such efforts. However, the more interesting questions are about how and why polycentricity varies across metropolitan areas. Whereas we provided some suggestive evidence that some metropolitan characteristics might play significant roles in explaining differences in spatial structures and their trajectories across metropolitan areas, future studies need to explore the statistical relationships by expanding the geographic scope of the study and focusing on a larger number of metropolitan areas: Is there a consistent relationship between metropolitan size and number of centers?; Is the degree of centralization or dispersion and the evolution of urban spatial structure explained by path dependence (or the unique development history of each metropolitan areas), physical geography, industry mix, local land use policy, transport infrastructure investments, general economic trends, or something else?

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Tables

Table 1. Employment and population growth of the four regions

<table>
<tr><th rowspan="2">Region</th><th rowspan="2">Year</th><th colspan="3">Employment</th><th colspan="2">Population</th></tr>
<tr><th>Total Number</th><th>5-year Change (%)</th><th>Decade Change (%)</th><th>Total Number</th><th>Decade Change (%)</th></tr>
<tr><td rowspan="5">Los Angeles</td><td>1990</td><td>7,137,735</td><td></td><td></td><td>14,531,513</td><td></td></tr>
<tr><td>1995</td><td>7,495,021</td><td>5.0</td><td></td><td></td><td></td></tr>
<tr><td>2000</td><td>8,296,734</td><td>10.7</td><td>16.2</td><td>16,373,645</td><td>12.7</td></tr>
<tr><td>2005</td><td>8,712,612</td><td>5</td><td>16.3</td><td rowspan="2">17,577,378</td><td rowspan="2">13.8</td></tr>
<tr><td>2009</td><td>8,366,348</td><td>-4.0</td><td>0.8</td></tr>
<tr><td rowspan="5">San Francisco</td><td>1990</td><td>3,399,818</td><td></td><td></td><td>6,252,591</td><td></td></tr>
<tr><td>1995</td><td>3,683,500</td><td>8.3</td><td></td><td></td><td></td></tr>
<tr><td>2000</td><td>4,380,182</td><td>18.9</td><td>28.8</td><td>7,092,595</td><td>13.4</td></tr>
<tr><td>2005</td><td>4,197,545</td><td>-4.2</td><td>14</td><td rowspan="2">7,257,729</td><td rowspan="2">8.8</td></tr>
<tr><td>2009</td><td>3,953,227</td><td>-5.8</td><td>-9.7</td></tr>
<tr><td rowspan="5">San Diego</td><td>1990</td><td>1,102,650</td><td></td><td></td><td>1,682,953</td><td></td></tr>
<tr><td>1995</td><td>1,208,623</td><td>9.6</td><td></td><td></td><td></td></tr>
<tr><td>2000</td><td>1,448,164</td><td>19.8</td><td>31.3</td><td>2,028,031</td><td>20.5</td></tr>
<tr><td>2005</td><td>1,559,792</td><td>7.7</td><td>29.1</td><td rowspan="2">2,335,271</td><td rowspan="2">25.9</td></tr>
<tr><td>2009</td><td>1,578,355</td><td>1.2</td><td>9.0</td></tr>
<tr><td rowspan="5">Sacramento</td><td>1990</td><td>685,943</td><td></td><td></td><td>2,497,314</td><td></td></tr>
<tr><td>1995</td><td>838,391</td><td>22.2</td><td></td><td></td><td></td></tr>
<tr><td>2000</td><td>962,265</td><td>14.8</td><td>40.3</td><td>2,813,076</td><td>12.6</td></tr>
<tr><td>2005</td><td>1,057,669</td><td>9.9</td><td>26.2</td><td rowspan="2">2,986,821</td><td rowspan="2">12.5</td></tr>
<tr><td>2009</td><td>1,064,794</td><td>0.7</td><td>10.7</td></tr>
</table>

Note: Population in 1990 and 2000 are from the 1990 and 2000 U.S. Census of Population, respectively. Population in 2005 is from the American Community Survey (ACS) 5-year average estimates for 2005-2009.

Table 2. Minimum Density Cutoffs, number and other basic characteristics of employment centers by year, metro area

Region	Year	95%/10K Centers				99%/20K Centers					
		Minimum Density Cutoff	Total number	Mean Persistence Score*	Minimum Density Cutoff	Total number	Mean Persistence Score*	Total Employment within centers	Percentage of employment within centers (%)	Average number of jobs per center	Average Density (Jobs per acre)
	1990	9.5	45	0.51	22.2	13	0.54	1,154,639	16.2	88,818	37.5
	1995	9.6	48	0.76	22.9	15	0.66	1,229,904	16.4	81,130	37.7
Los Angeles	2000	10.2	53		23.9	18		1,420,410	17.1	78,912	38.5
	2005	10.5	53	0.72	23	18	0.79	1,380,418	15.8	76,690	36.5
	2009	9.3	48	0.72	21.6	13	0.60	1,226,579	14.7	94,352	34.6
	1990	7.1	24	0.75	17.5	9	0.59	829,456	24.4	92,162	38.8
	1995	7.3	28	0.74	18.6	6	0.65	860,108	23.4	143,351	47
San Francisco	2000	8.6	30		20.5	9		1,084,128	24.8	120,459	45.1
	2005	7.8	30	0.74	19.3	11	0.56	935,569	22.3	85,052	36.3
	2009	7.4	30	0.71	16.3	11	0.72	873,024	22.1	79,366	38.3
	1990	6.4	14	0.53	14.2	3	0.61	167,888	15.2	83,944	40.7
	1995	6.8	9	0.51	14.4	3	0.73	159,936	13.2	53,312	34.9
San Diego	2000	8.3	13		16.9	3		242,911	16.8	80,970	39.8
	2005	8.3	13	0.86	17.2	3	1	235,274	15.1	78,425	38.3
	2009	7.9	13	0.69	16.5	4	0.69	230,395	14.6	76,798	37.0
Sacramento	1990	2.4	4	0.40	6.7	2	0.41	163,444	9.7	81,722	20.5

	1995	2.4	7	0.76	7.5	3	0.8	214,471	25.6	71,490	19.4
	2000	2.8	7		8.3	2		258,961	26.9	129,481	19.2
	2005	2.9	8	0.78	8.2	2	0.65	278,230	26.3	139,115	16.3
	2009	2.9	7	0.84	7.7	2	0.85	232,882	21.9	116,441	14.7

Note*: The 2000 center boundaries are used as references

Table 3. Monocentric (mono) and polycentric (poly) density functions, by metro areas (1990)

	Los Angeles			San Francisco			San Diego			Sacramento	
	Mono	Poly		Mono	Poly		Mono	Poly		Mono	Poly
Distance to CBD											
LA CBD	-0.0348***	-0.0348***	SF CBD	-0.0492***	-0.0358***	SD CBD	-0.0967***	-0.0836***	Sac CBD	-0.0324***	-0.00836**
	(-42.68)	(-42.68)		(-25.78)	(-17.17)		(-25.52)	(-18.81)		(-13.55)	(-3.27)
Inverse of distance to subcenters											
John-Wayne Airport		7.155***	San Jose downtown		5.652***	Eastern SD		3.156***	Rancho Cordova		8.759***
		(16.97)			(7.28)			(5.53)			(18.95)
West Los Angeles		3.580***	West Oakland		5.985***						
		(6.80)			(9.51)						
Pasadena		5.118***	San Jose State Univ.		5.331***						
		(8.84)			(6.01)						
Burbank (Hollywood studios)		2.600***	Stanford Univ.		4.441***						
		(3.95)			(7.19)						
LAX		6.165***									
		(10.23)									
Woodland Hills		2.912***									
		(4.85)									
Long Beach downtown		8.354***									
		(13.09)									
_cons	-0.0644	-2.226***	_cons	-0.371***	-1.769***	_cons	0.320**	-0.286	_cons	-2.376***	-3.686***
	(-1.25)	(-24.40)		(-4.41)	(-15.71)		(2.81)	(-1.82)		(-28.46)	(-35.53)

N	5685	5685	3652	3652	1409	1409	2175	2175
adj. R-sq	0.243	0.347	0.154	0.267	0.316	0.3301	0.077	0.208
SSR	29305.7	25248.5	18605.5	16101.8	5703.1	5581.8	9021.8	7741.8
q		7		4		1		1
N-q-2		5676		3646		1406		2172
F(q, N-q-2)		130.3***		141.7***		30.5***		359.1***
Wald test Chi2(1) statistics		644.09***		237.43***		53.51***		286.94***

t statistics in parentheses; * p<0.05, **p<0.01, *** p<0.001

Note: The F value is computed as

$$F(q, N-p) = \frac{(\text{SSR}` - \text{SSR}")/q}{\text{SSR}"/(N-p)}$$

where SSR` and SSR" are restricted (monocentric) and unrestricted (polycentric) sums of squared residuals, N is sample size, p is the number of parameters estimated in the unrestricted model, and q is the number of restrictions in the restricted model. See detailed discussions in Small and Song (1994: 303−304).

Table 4. Monocentric (mono) and polycentric (poly) density functions, by metro areas (2009)

	Los Angeles			San Francisco			San Diego			Sacramento	
	Mono	Poly		Mono	Poly		Mono	Poly		Mono	Poly
Distance to CBD											
LA CBD	-0.0343*** (-44.98)	-0.0179*** (-18.77)	SF CBD	-0.0492*** (-27.75)	-0.0261*** (-11.46)	SD CBD	-0.0997*** (-29.08)	-0.0857*** (-20.72)	Sac CBD	-0.0371*** (-18.51)	-0.0215*** (-9.81)
Inverse of distance to subcenters											
John-Wayne Airport		7.984*** (18.20)	San Jose downtown		4.035*** (7.96)	Eastern SD		1.544** (2.60)	Rancho Cordova		8.718*** (15.26)
West LA		2.387*** (5.49)	West Oakland		5.241*** (8.35)	Sorrento Valley		2.992*** (4.90)			
Pasadena		4.314*** (7.97)	San Jose State Univ.		6.284*** (8.47)						
Burbank (Hollywood studios)		1.861** (2.86)	Stanford Univ.		2.318*** (3.78)						
LAX		5.434*** (8.96)	South San Francisco		3.600*** (5.55)						
Woodland Hills		2.073** (3.16)	Walnut Creek		3.039*** (5.11)						
Long Beach		7.956*** (12.38)	Pleasanton		1.461* (2.01)						
Encino-Sherman Oaks		1.322 (1.96)	Redwood Shores		3.517*** (4.97)						

			Central San Ramon		0.133						
					(0.18)						
_cons	0.222***	-2.287***	_cons	-0.104	-2.268***	_cons	0.812***	0.112	_cons	-1.989***	-2.923***
	(4.40)	(-24.63)		(-1.27)	(-16.11)		(7.74)	(0.47)		(-27.95)	(-31.80)
N	6616	6616		4139	4139		1639	1639		3021	3021
adj. R-sq	0.234	0.3227		0.157	0.271		0.3402	0.365		0.102	0.166
SSR	33833.7	29904.9		21081.2	18246.4		6421.7	6260.4		12477.6	11584.1
q		8			9			2			1
n-q-2		6606			4128			1635			3018
F(q, n-q-2)		108.48***			71.26***			21.06***			232.79***
Wald test Chi2(1) statistics		601.84***			338.05***			49.16***			157.75***

t statistics in parentheses; * p<0.05, **p<0.01, *** p<0.001

Note: The newly identified centers in 2009 are highlighted in the table.

Table 5. Polycentric density functions and employment growth pattern of centers of Los Angeles (using 2000 centers)

	Polycentric density function					Wald tests of estimated coefficients; Growth rate of centers							
	lned90	lned95	lned00	lned05	lned09		1990 vs. 2000	2000 vs. 2009	1990 vs. 2009	1990 vs. 1995	1995 vs. 2000	2000 vs. 2005	2005 vs. 2009
CBD	-0.0107***	**-0.0109*****	**-0.0120*****	-0.0129***	-0.0128***	Wald test: Chi2			**8.16****	0.16	**5.52***	3.36	0.14
	(-10.35)	(-10.65)	(-11.71)	(-13.01)	(-13.07)	Growth rate (%)	-6.95	-9.88	-16.14	-7.01	0.06	-2.94	-7.15
John-Wayne Airport	**4.787*****	**5.089*****	5.357***	5.502***	5.495***	Wald test: Chi2			**8.52****	**8.53****	3.71	1.25	0.01
	(9.96)	(10.40)	(10.81)	(11.20)	(11.38)	Growth rate (%)	48.10	-4.26	41.79	17.58	25.96	4.46	-8.35
West Los Angeles	2.899***	2.856***	2.770***	2.878***	3.034***	Wald test: Chi2			0.56	0.49	1.52	1.97	1.13
	(5.29)	(5.11)	(4.88)	(5.10)	(5.48)	Growth rate (%)	24.39	-3.51	20.02	15.16	8.02	5.19	-8.28
Pasadena	3.381***	**3.419*****	**3.118*****	**3.338*****	3.290***	Wald test: Chi2			0.18	0.15	**13.19*****	**4.03***	0.09
	(5.81)	(5.77)	(5.18)	(5.58)	(5.60)	Growth rate (%)	31.77	-9.07	19.82	21.62	8.35	4.47	-12.96
Burbank (Hollywood studios)	2.688***	2.549***	2.438***	2.549***	1.911**	Wald test: Chi2			1.64	1.83	0.98	0.51	1.3
	(4.19)	(3.91)	(3.68)	(3.87)	(3.04)	Growth rate (%)	18.32	5.47	24.78	23.19	-3.95	11.81	-5.67

LAX	3.445***	3.419***	**3.345*****	**3.047*****	**2.801*****	Wald test: Chi2			**10.37****	0.03	0.32	**11.1****	**6.44***
	(5.76)	(5.61)	(5.41)	(4.95)	(4.62)	Growth rate (%)	4.23	-28.59	-25.57	-19.56	29.57	**-20.53**	**-10.14**
Woodland Hills	4.101***	3.968***	3.675***	3.719***	3.706***	Wald test: Chi2			2.57	0.66	*3.28*	0.08	0.01
	(6.85)	(6.52)	(5.96)	(6.09)	(6.18)	Growth rate (%)	15.75	-29.85	-18.80	-2.23	18.39	-22.25	-9.78
Long Beach downtown	**5.625*****	5.511***	5.434***	5.254***	**5.105*****	Wald test: Chi2			**7.09****	0.85	0.28	1.56	2.63
	(8.62)	(8.29)	(8.05)	(7.81)	(7.72)	Growth rate (%)	8.50	-1.57	**6.79**	16.47	-6.84	7.12	-8.12
Commerce	7.359***	**7.244*****	**7.036*****	**6.756*****	**6.429*****	Wald test: Chi2			**36.3*****	1.76	**5.42***	**8.02****	**15.62*****
	(11.72)	(11.33)	(10.84)	(10.47)	(10.13)	Growth rate (%)	12.72	-50.83	-44.58	12.89	**-0.15**	**-40.52**	**-17.34**
Torrance	3.807***	3.883***	3.735***	3.839***	3.871***	Wald test: Chi2			0.15	0.53	0.77	0.9	0.17
	(5.52)	(5.53)	(5.24)	(5.41)	(5.54)	Growth rate (%)	41.110	-30.81	-2.36	12.32	25.63	-20.46	-13.01
Anaheim	7.247***	7.264***	7.302***	7.204***	7.210***	Wald test: Chi2			0.03	0.03	0.12	0.87	0.01
	(13.48)	(13.28)	(13.15)	(13.06)	(13.29)	Growth rate (%)	58.43	-15.72	33.53	27.15	24.61	-0.28	-15.48
Santa Monica	1.034	0.930	0.855	0.807	0.686	Wald test: Chi2			1.16	0.59	0.91	0.07	0.24

	(1.19)	(1.05)	(0.95)	(0.90)	(0.78)	Growth rate (%)	61.12	-20.17	28.62	29.79	24.14	-2.83	-17.85
_cons	-2.903***	-2.819***	-2.620***	-2.490***	-2.392***								
	(-30.03)	(-29.22)	(-27.12)	(-26.44)	(-25.97)								
N	5675	5882	6083	6436	6612								
adj. R-sq	0.383	0.371	0.361	0.363	0.355								

Note: Coefficients for each center that change significantly between study periods (i.e., 1990 vs. 2009, 1990 vs. 1995; 1995 vs. 2000, 2000 vs. 2005, and 2005 vs. 2009) (on the left side) and the corresponding Chi-square statistics of Wald tests and growth rate of the center (on the right side) are in bold. t statistics in parentheses

* p<0.05 ** p<0.01 *** p<0.001

Table 6. Polycentric density functions and employment growth pattern of centers of San Francisco (using 2000 centers)

	Polycentric density function					Wald tests of estimated coefficients; Growth rate of centers							
	lned90	lned95	lned00	lned05	lned09		1990 vs. 2000	2000 vs. 2009	1990 vs. 2009	1990 vs. 1995	1995 vs. 2000	2000 vs. 2005	2005 vs. 2009
CBD	-0.0256***	-0.0262***	-0.0270***	-0.0276***	-0.0283***	Wald test: Chi2			*2.81*	0.5	0.62	0.35	0.85
	(-11.00)	(-11.12)	(-11.52)	(-12.13)	(-12.85)	Growth rate (%)	20.82	-23.47	-7.54	6.90	13.03	-12.59	-12.45
San Jose downtown	3.295***	**3.507*** **	**3.737*** **	**3.398*** **	3.022***	Wald test: Chi2			**4.05***	*2.8*	**4.61***	**8.64** **	*3.14*
	(5.71)	(5.93)	(6.16)	(5.68)	(5.16)	Growth rate (%)	44.02	-30.27	0.43	15.54	**24.65**	**-25.10**	-6.91
West Oakland	5.581***	5.553***	5.552***	**5.457*** **	**5.226*** **	Wald test: Chi2			2.27	0.05	0	0.41	**4.23***
	(8.96)	(8.71)	(8.53)	(8.51)	(8.31)	Growth rate (%)	16.54	-27.01	-14.93	11.06	4.93	-8.98	**-19.81**
San Jose State Univ.	5.721***	5.629***	5.866***	6.019***	6.074***	Wald test: Chi2			1.22	0.32	1.9	0.88	0.08
	(7.25)	(6.97)	(7.09)	(7.38)	(7.59)	Growth rate (%)	24.06	-21.58	-2.72	5.12	18.01	1.40	-22.66
Stanford Univ.	2.935***	2.913***	2.904***	2.780***	2.702***	Wald test: Chi2			1.11	0.01	0	0.45	0.24
	(4.39)	(4.25)	(4.13)	(4.02)	(3.97)	Growth rate (%)	4.46	-22.70	-19.25	-5.37	10.38	-23.21	0.67

South SF	4.429***	4.377***	4.376***	4.388***	4.069***	Wald test: Chi2			1.81	0.17	0	0	2.15
	(7.01)	(6.77)	(6.61)	(6.72)	(6.34)	Growth rate (%)	55.63	-27.73	12.47	22.78	26.75	-14.11	-15.86
Mountain View	3.863***	3.212***	3.334***	3.027***	3.312***	Wald test: Chi2			*3.72*	2	0.47	*3.56*	0.62
	(4.80)	(3.95)	(4.00)	(3.68)	(4.06)	Growth rate (%)	41.28	-52.46	-32.83	17.20	20.55	-35.78	-25.97
Walnut Creek	3.772***	3.538***	**3.462*****	**3.864*****	3.833***	Wald test: Chi2			0.07	1.85	0.23	**5.61***	0.07
	(6.02)	(5.53)	(5.29)	(6.01)	(6.07)	Growth rate (%)	62.01	-22.89	24.92	34.23	20.70	**-8.36**	-15.85
_cons	-2.511***	-2.412***	-2.309***	-2.205***	-2.118***								
	(-18.23)	(-17.22)	(-16.41)	(-16.12)	(-15.90)								
N	3647	3727	3895	4081	4140								
adj. R-sq	0.289	0.274	0.271	0.268	0.269								

Note: Coefficients for each center that change significantly between study periods (i.e., 1990 vs. 2009, 1990 vs. 1995; 1995 vs. 2000, 2000 vs. 2005, and 2005 vs. 2009) (on the left side) and the corresponding Chi-square statistics of Wald tests and growth rate of the center (on the right side) are in bold. t statistics in parentheses

* $p<0.05$ ** $p<0.01$ *** $p<0.001$

Table 7. Polycentric density functions and employment growth pattern of centers of San Diego (using 2000 centers)

	Polycentric density function					Wald tests of estimated coefficients; Growth rate of centers							
	lned90	lned95	lned00	lned05	lned09		1990 vs. 2000	2000 vs. 2009	1990 vs. 2009	1990 vs. 1995	1995 vs. 2000	2000 vs. 2005	2005 vs. 2009
CBD	-0.0811***	-0.0800***	-0.0810***	-0.0838***	-0.0866***	Wald test: Chi2			*3.22*	2.68	1.71	0.18	0.2
	(-17.80)	(-17.33)	(-17.91)	(-19.40)	(-21.08)	Growth rate (%)	31.31	-13.71	13.31	-8.94	-5.23	17.65	11.61
Eastern SD	**2.209*** **	**2.272*** **	1.971**	1.698**	**1.217***	Wald test: Chi2			**6.21***	**6.83** **	1.35	0.32	0.02
	(3.69)	(3.66)	(3.26)	(2.85)	(2.11)	Growth rate (%)	21.17	-3.19	17.30	0.24	-3.42	25.24	-3.25
Sorrento Valley	1.846**	**1.516** **	**1.929*** **	2.411***	2.526***	Wald test: Chi2			1.55	1.02	**5.24***	2.1	0.54
	(3.18)	(2.67)	(3.39)	(4.29)	(4.62)	Growth rate (%)	76.65	-7.98	62.54	-7.76	-0.24	30.91	34.94
_cons	-0.421*	-0.284	-0.156	0.0338	0.217								
	(-2.50)	(-1.67)	(-0.93)	(0.21)	(1.39)								
N	1405	1424	1493	1586	1638								
adj. R-sq	0.324	0.308	0.310	0.330	0.349								

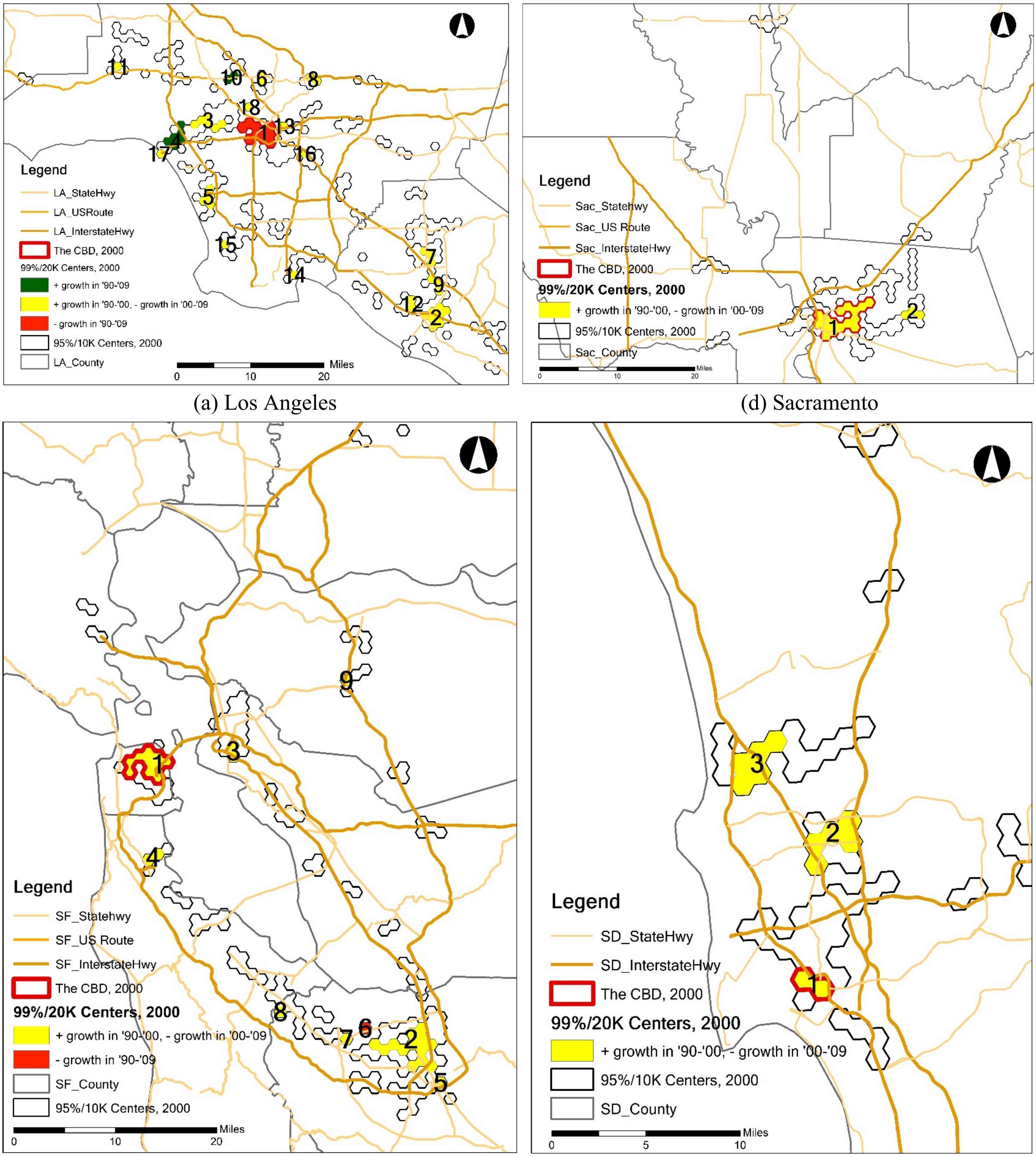
Note: Coefficients for each center that change significantly between study periods (i.e., 1990 vs. 2009, 1990 vs. 1995; 1995 vs. 2000, 2000 vs. 2005, and 2005 vs. 2009) (on the left side) and the corresponding Chi-square statistics of Wald tests and growth rate of the center (on the right side) are in bold. t statistics in parentheses

* p<0.05 ** p<0.01 *** p<0.001

Table 8. Polycentric density functions and employment growth pattern of centers of Sacramento (using 2000 centers)

	Polycentric density function					Wald tests of estimated coefficients; Growth rate of centers							
	lned90	lned95	lned00	lned05	lned09		1990 vs. 2000	2000 vs. 2009	1990 vs. 2009	1990 vs. 1995	1995 vs. 2000	2000 vs. 2005	2005 vs. 2009
CBD	**-0.0194*****	**-0.0153*****	-0.0160***	**-0.0198*****	**-0.0220*****	Wald test: Chi2			1.29	**4.99***	0.54	**11.11****	**5.45***
	(-7.26)	(-6.64)	(-7.02)	(-8.88)	(-10.01)	Growth rate (%)	29.74	-14.67	10.71	12.53	15.30	-1.07	-13.75
Rancho Cordova	**7.782*****	8.208***	8.513***	8.608***	**8.668*****	Wald test: Chi2			**5.02***	2.12	1.66	0.14	0.04
	(12.97)	(13.83)	(14.23)	(14.71)	(15.12)	Growth rate (%)	49.44	-31.16	**2.87**	26.07	18.54	-16.03	-18.02
_cons	-3.294***	-3.394***	-3.242***	-3.037***	-2.898***								
	(-31.98)	(-35.02)	(-33.48)	(-32.24)	(-31.28)								
N	2169	2648	2748	2951	3023								
adj. R-sq	0.152	0.134	0.138	0.154	0.167								

Note: Coefficients for each center that change significantly between study periods (i.e., 1990 vs. 2009, 1990 vs. 1995; 1995 vs. 2000, 2000 vs. 2005, and 2005 vs. 2009) (on the left side) and the corresponding Chi-square statistics of Wald tests and growth rate of the center (on the right side) are in bold. t statistics in parentheses
* p<0.05 ** p<0.01 *** p<0.001



(a) Los Angeles (d) Sacramento

(b) San Francisco (c) San Diego

Figure 1. Employment centers (2000) in the four metro areas

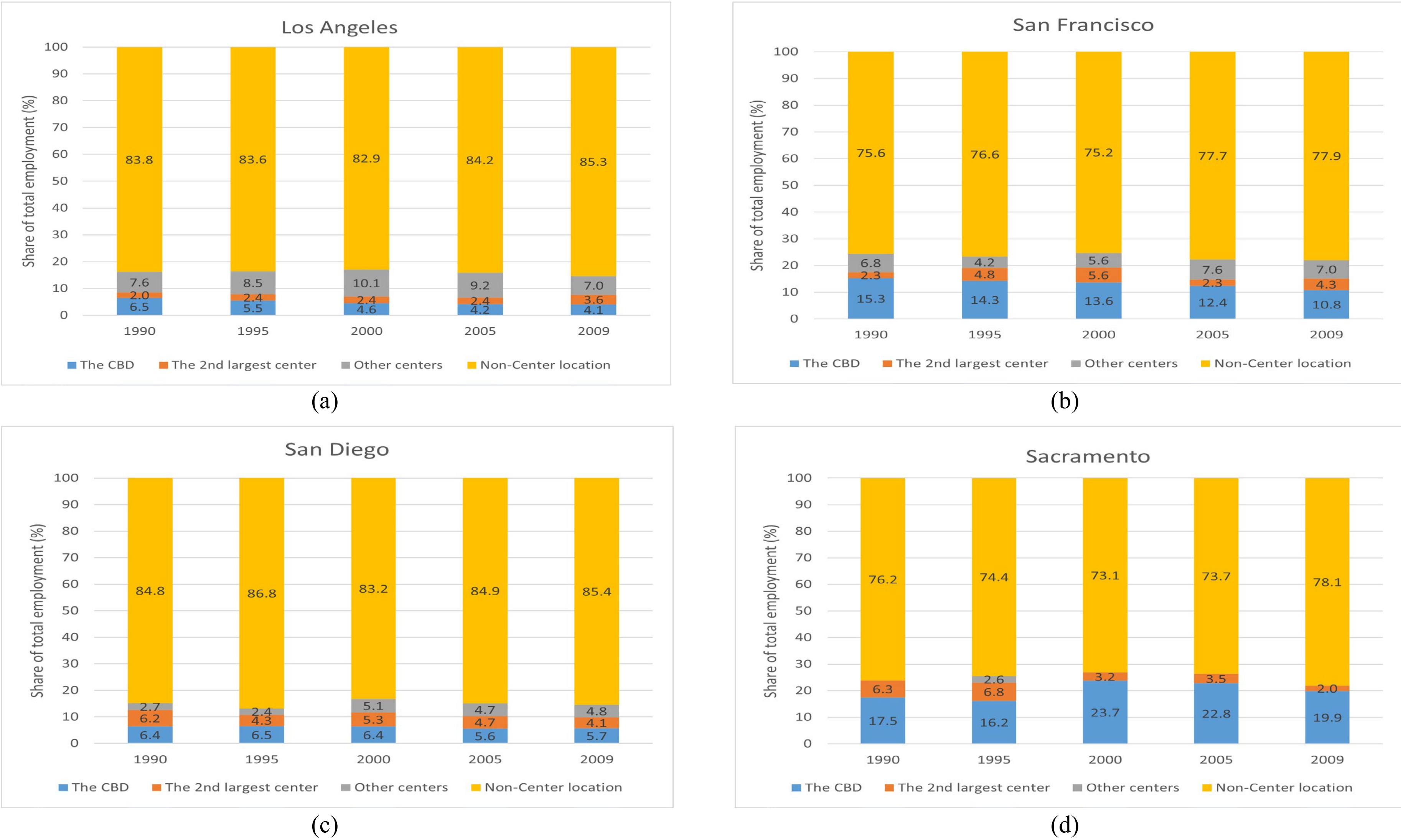
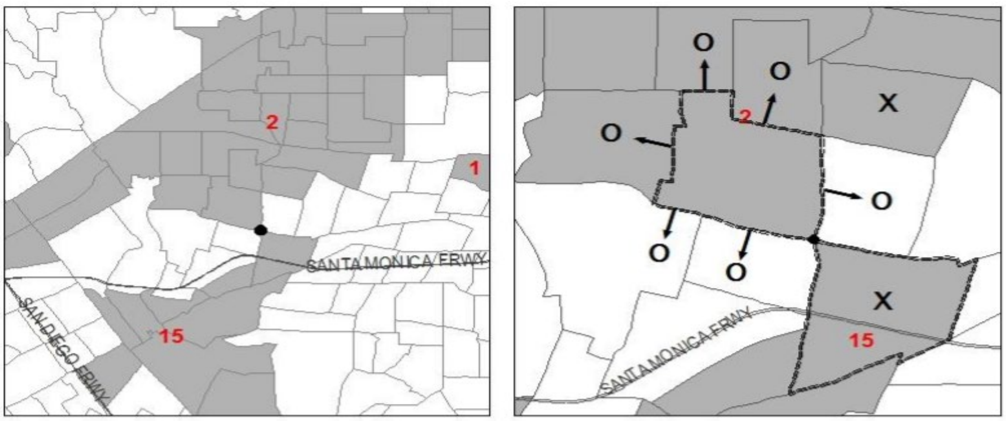


Figure 2. Changes in Employment distribution among the CBD, the 2nd largest center, other centers and non-center locations, by year and metro area (99%/20K centers)

Appendix: Advantages of using regular hexagons as the unit of analysis in identifying employment centers

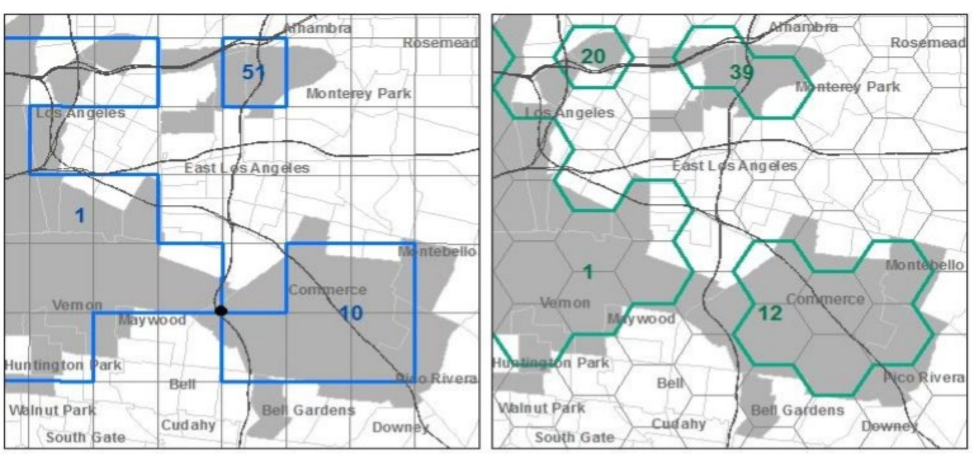
In this appendix, we illustrate the advantages of employing a hexagon with a few simple illustrative examples. Figure A1(a) shows two employment centers (Centers 2 and 15) identified by the Giuliano and Small (1991) method using census tracts as a unit of analysis. In this case, tracts meeting the density criterion share a common point. Figure A1 (b) illustrates this common point in greater detail. Six arrows emanating from Center 2 census tract with black boundary show the 'O'-labeled census tracts which share common boundaries. In the meantime, two 'X'-labeled census tracts only share common points with Center 2 census tract. Whether to consider Centers 2 and 15 as one center depends on the arbitrary choice of whether a point constitutes a common boundary.



(a) (b)

Figure A1. Ambiguity in defining adjoining census tracts

Figure A2 shows another group of centers. The grey shading displays the center boundaries, defined based on census tracts. In Figure A2(a), the area is overlaid with one-square-mile grids, and the blue outlines show the grid units that meet the Giuliano and Small criteria. It can be seen that the same problem of common points appears. Figure A2 (b) shows the same area, but this time centers were identified with one-square-mile hexagons. Green outlines show the areas that meet the Giuliano and Small criteria. In this case, each identified center has unambiguous boundaries.



(a) (b)

Figure A2. Defined employment centers based on one-square-mile grids (a) and hexagons (b)