# URBAN STRUCTURE: ITS ROLE IN URBAN GROWTH, NET NEW BUSINESS FORMATION AND INDUSTRIAL CHURN

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***Abstract -*** *Cities are the "engines of growth" because entrepreneurial and creative activities are concentrated in cities. This suggests that cities grow by hosting new businesses and "churning" industries advantageously. In so doing, cities need to adapt their spatial structure to mitigate negative externalities. Our previous paper (Lee and Gordon 2007) found that the links between urban structure and growth vary across metro size: more clustering in small metros and more dispersion in large metros were associated with faster employment growth. In this paper, we extend our research to investigate to what extent urban spatial structure variables – dispersion and polycentricity – influence net new business formation (NNBF) and industrial "churning" in a cross-section of 79 U.S. metropolitan areas in the 2000s. The results of least squares regression and locally weighted regression analyses are mixed. OLS results for recent years fail to replicate out results for the 1990s. But applying a more powerful LOESS approach does give results for spatial impacts on NNBF and industrial churning that are consistent with the links between spatial structure and urban growth found in the earlier paper.*

***Key-Words:*** URBAN SPATIAL STRUCTURE, URBAN GROWTH, NET NEW BUSINESS FORMATION (NNBF), INDUSTRIAL CHURN.

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## 1. INTRODUCTION: URBAN SIZE, SPATIAL STRUCTURE AND GROWTH

What do we know about cities and economic growth? First, cities play a critical role in economic development. They are the "engines of growth." They are places where, for a variety of reasons, people do their best work. Ever since Joseph Schumpeter, economists have recognized the key role of entrepreneurs. They specialize in discovery, the key economic activity in Schumpeter's view. This involves discovering new products and services as well as how to bring them to market in new and better ways. At least as important as Schumpeter's contribution is Hayek's insistence that local knowledge spread among large numbers of decentralized actors who implement the many important details, including supply chains. The unique spatial arrangements within urban areas can be expected to form in ways that facilitate the flow of ideas and innovation, enabling successful cities to be congenial hosts to innovative and entrepreneurial activities.

Second, cities change slowly but most do adapt. Different urban forms are associated with different technologies. In particular, dramatically improved mobility by cars and highways freed up various economic activities from the urban center and expanded urban areas to an unprecedented extent in the second half of the last century. Many urban researchers agree that metropolitan spatial structure underwent a "qualitative change" toward more polycentric and/or dispersed forms (Gordon and Richardson, 1996; Anas, Arnott, and Small, 1998; Clark, 2000). It is also apparent that European planners increasingly view polycentric development as a spatial planning strategy to promote economic efficiency and urban sustainability (Waterhout, Zonneveld, and Meijers, 2005; Meijers, 2008). To date, however, and with the exception of support for metropolitan area-wide average "density", little empirical research has been done on the relationships between urban form and economic efficiency.

Which urban structure will be most congenial to creative and entrepreneurial spirits? Which ones will be the future engines of growth? Another way to pose the question is to ask what role spatial structure plays. Is one particular type of urban form more efficient than another? Or is efficient spatial structure contingent on the size and other attributes of each metropolitan area? These are the questions that we attempt to address in this paper.

Jane Jacobs' (1969) discussion of successful neighborhoods articulated Schumpeterian (and perhaps Hayekian) themes. The idea that spontaneous neighborhood organization is productive and that this is how the stock of knowledge is best mobilized has recently begun to be addressed by urban economists (Glaeser et al., 1992; Glaeser and Gottlieb, 2009). Substantial evidence has accumulated on the existence and extent of agglomeration economies that arise from various sources, including localization economies and urbanization economies (for surveys of the literature, see Moomaw, 1983; Gerking, 1994; Melo, Graham, and Noland, 2009). In general, firms in large cities can enjoy greater productivity due to lower production costs and/or more innovative opportunities. Recent literature tends to emphasize the role of innovative process localized within urban clusters (Malmberg, 1996; Porter, 2000). Furthermore, workers also have more chances to learn and acquire skills in large urban agglomerations that make higher returns possible (Glaeser, 1999).

However, there are also costs associated with urban size. Firms and households in large cities encounter negative externalities including congestion, pollution as well as high land prices. Thus, there is a need for a mechanism that mitigates some of the negative externalities for a large city to accommodate continued economic growth. Urban economic theories suggest that spatial transformation from monocentric to polycentric structure is one mechanism of abating agglomeration diseconomies (Sasaki and Mun, 1996; Fujita, Thisse, and Zenou, 1997). In a city with multiple employment centers, firms in subcenters can avoid the external costs of central location while still benefiting from agglomeration economies (Richardson, 1988). As the negative externalities of city size grow with the size of urban agglomeration in general, large cities with more congestion tend to have a more polycentric structure (Fujita and Ogawa, 1982; McMillen and Smith, 2003).

Yet, Gordon and Richardson (1996) suggested that generalized spatial dispersion of economic activities will be more likely than subcentering if agglomeration opportunities are ubiquitous throughout the metropolitan area. They showed that Los Angeles can be better described as a dispersed than a polycentric metropolis. In another study (Gordon, Richardson, and Jun, 1991), the authors suggested that these emerging urban forms may be more efficient than a monocentric structure in checking the growth of commuting time by providing more flexible location choices for households and firms. A recent review of agglomeration economies and spatial equilibrium (Glaeser and Gottlieb, 2009) emphasized the importance of an elastic housing supply in determining urban economic growth.

Notwithstanding the importance of urban spatial structure, much of the empirical research on the determinants of urban growth or productivity still invokes city size as a proxy for the benefits that Jacobs emphasized (Melo, Graham, and Noland, 2009). Others settle for county-level (Ellison and Glaeser, 1997) or metropolitan-level average densities (Ciccone and Hall, 1996; Carlino and Chatterjee, 2002). However, average population or employment density represents an inadequate summary of the complex spatial arrangements and dynamics of metropolitan areas. Galster et al. (2001) show that there exist many dimensions of urban form. The modest empirical research relating urban form to economic efficiency and urban growth can be attributed to the absence of appropriate measures of detailed urban structure and relevant data. To address that gap in the literature, this paper provides relatively simple measures of urban spatial structure and presents tests of how these spatial measures are associated with the success of cities as manifested by their continuing ability to attract labor and capital and to spawn ideas that create new businesses and industries.

Our previous paper (Lee and Gordon, 2007) contributed to narrowing the gap between growth economics and urban economics. We suggested a way to test the links between urban size, spatial structure and growth by utilizing our unique spatial data set for the 79 largest U.S. metropolitan areas. We found evidence that urban forms evolve to accommodate growth; spatial patterns emerge that accommodate and limit the road and highway congestion that comes with greater urban scale. We found that the links between spatial structure indicators and urban growth vary across metro size: more clustering in small metros and more dispersion in large metros were associated with faster employment growth – after controlling other supply side variables and regional location.

Our growth investigations suggested that Schumpeter's "gales of creative destruction" have a spatial aspect. And this finding places a premium on flexible land markets and the open-ended evolution of urban structure. In this paper, we extend this work on the links between urban spatial structure and employment growth in a cross-section of 79 U.S. metropolitan areas to also consider measures of industrial change and entrepreneurial activities. We examine the spatial impacts on these growth indicators in the early 2000s applying both ordinary least squares (OLS) and locally weighted regression (LOESS) techniques.

The remainder of this paper is organized as follows. In Section 2, we discuss our growth equations and the importance of industrial churning and net new business formation (NNBF) in metropolitan growth. Section 3 briefly shows how we developed the measures of metropolitan spatial structure. Section 4 presents the results of the OLS and LOESS estimations, followed by a conclusion and discussion section.

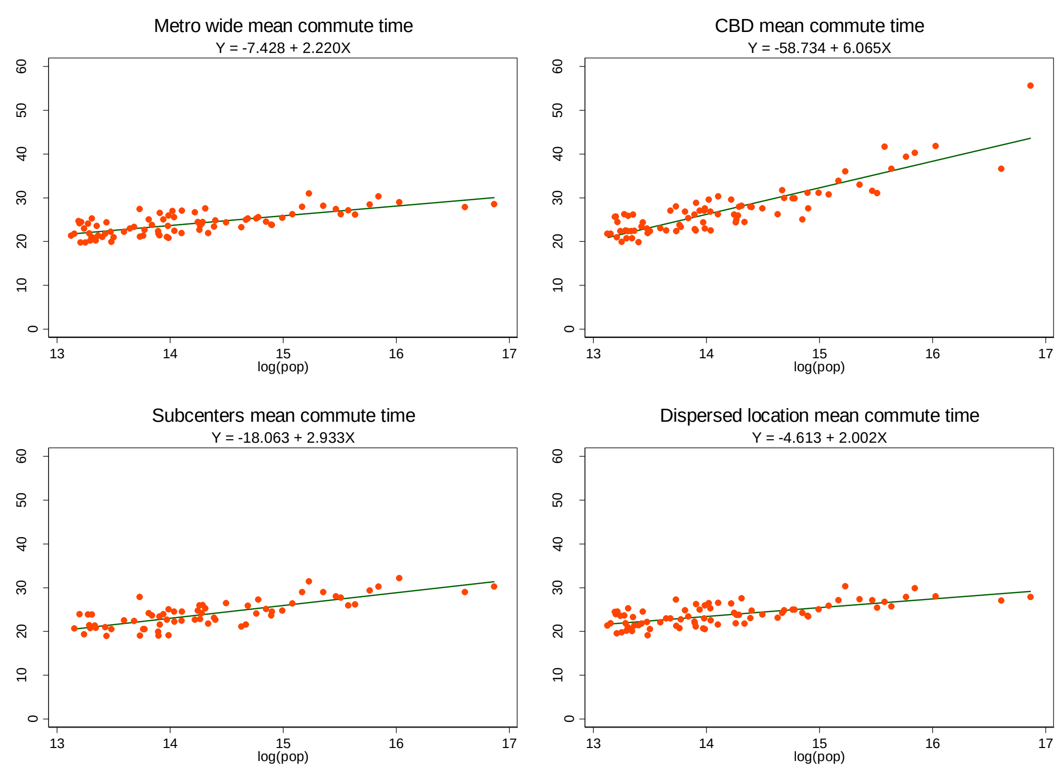
## 2. GROWTH EQUATIONS, INDUSTRIAL CHURNING AND NNBF

Our empirical analysis in this paper involves testing whether or not spatial structure can be linked to industrial churning and net new business formation (NNBF) in metropolitan areas. We also compare these results to the model's explanation of metropolitan employment growth.

We base our empirical regression models on a supply-side urban economic growth model developed by Glaeser and his colleagues (Glaeser, Scheinkman, and Shleifer, 1995; Glaeser, 2000; Glaeser and Shapiro, 2003). In this type of growth model, a city's favorable attributes promote employment growth in three ways: 1) becoming more important in the production process; 2) attracting more consumers; or 3) facilitating faster technological growth. Their empirical analysis suggests that higher education among residents, warmer and drier climate, and an automobile-oriented transportation system are three key factors that contributed to faster growth in U.S. cities in the 1990s.

We modify this supply-side urban growth model to examine the effects of spatial structure variables on industrial churning and NNBF as well as employment growth. In particular, we hypothesize that the relationship between spatial variables and employment growth or its accompanying phenomena is contingent on metropolitan size, rather than assuming one global link. This hypothesis is based on the observation that commuting times are less sensitive to increasing metro size if employment is decentralized.

***Figure1: Mean commute time by workplace type vs. metro population size***




Note: Mean commuting time was calculated only for the drive-alone mode.

Figure 1 shows increasing mean commuting times of workers in different locations with the increase in metropolitan population size. The slope of the estimated semi-log regression line is apparently the steepest for CBD workers. The increase in average commuting time associated with a doubling metropolitan population size was approximately six minutes for CBD workers, but only about three minutes and two minutes for those workers commuting to subcenters and dispersed workplaces, respectively. This finding led us to conjecture that polycentric and dispersed spatial structure has an edge in mitigating congestion in large metropolitan areas.

As mentioned before, tests of this conjecture in our previous paper showed that in the 1990s more dispersed spatial form helped to accommodate faster growth in large metropolitan areas while a metropolitan area with more clustered spatial structure grew faster perhaps enjoying agglomeration economies when relatively small (Lee and Gordon, 2007). In this paper, we test if similar relationships exist between spatial structure and the two components of metropolitan economic growth, industrial churning and NNBF using data for the 2000s.

An interesting line of urban research by Duranton (2007) suggested that metro areas' ability to "churn" industries, letting go of the old and accommodating the new, accompanies their success. In his theoretical model, cross-industry innovations lead to the churning of industries across cities and cities grow or decline as a result of the realized local industrial churning. Glaeser has documented how Boston (Glaeser, 2005) and New York (Glaeser, 2009) have survived repeated economic crises and periods of decline triggered by technology shocks – such as the emergence of steamships, automobiles, and information technology – by reinventing themselves and accommodating the newly flourishing industries. Among the key assets needed to successfully respond to the recast challenges were a rich base of human capital and entrepreneurship in the two cities. Unlike these "reinventive" cities, it is not yet clear how Detroit will survive the decline of the traditional U.S. auto industry. Simon's (2004) cross-sectional analysis of 39 industries across 316 U.S. cities also demonstrated the role of industrial churning in the growth and decline of cities between 1977 and 1997, a period of burgeoning knowledge-intensive economies. The presence of larger manufacturing shares and a sector's own employment share in the beginning year was associated with slower subsequent growth, especially in the newer and skill-intensive industries.

Given these roles of industry turnover and entrepreneurial activities in long-term urban growth and prosperity, this paper examines what type of spatial structure is more accommodating to industry turnover and entrepreneurial activities. Does a more clustered and centralized spatial form promote innovation and entrepreneurial activities? Or does a more dispersed or polycentric structure represent flexible spatial arrangement accommodating more industrial turnover and new businesses? Is that relationship contingent on metropolitan size? We address these research questions with uniquely designed supply-side urban employment growth models, an OLS model with an interaction terms and a LOESS model.

The basic empirical model is presented in equation (1). Employment growth, industrial churning, and NNBF are alternately used as the dependent variables in this model. Explanatory variables include spatial structure variables as well as other covariates that are found in the literature. We use two spatial structure variables, indicating urban dispersion and polycentricity of employment that are estimated in the next section. To test whether or not the coefficients of the spatial variables vary across different metropolitan sizes, we include interaction terms involving the spatial measures and employment size in the OLS estimations.

Both spatial structure and size variables are centered (normalized) by subtracting mean values for ease of interpretation. We also estimate the varying coefficients of two spatial variables using LOESS. To estimate coefficients at each data point, we fit the base regression model to only half of the sample that are similar in employment size with the estimation points and give more weights to closer data points in the dimension of employment size. We used a 50-percent window size and the tricube weight function. The estimation results of both the OLS with interaction terms and the LOESS will show how the influence of spatial structure varies across different urban sizes.

$$Y = \alpha X + \beta_1 \log N + \beta_2 F + \beta_3 \log NF \tag{1}$$

, where *Y* denotes the dependent variables used in our models, employment growth, industrial churn, and NNBF in the early 2000s; *N* denotes employment size in the beginning year; *X* is a vector of metropolitan attributes listed in Table 3 including the constant; *F* is a vector of spatial structure variables – dispersion and polycentricity.

One estimation issue in the OLS regressions is the potential endogeneity of spatial variables. While we are testing the influence of spatial structure on urban growth, there is a possibility that urban growth in recent periods may affect the evolving spatial form of the metropolitan area. For instance, fast growing metropolitan areas tend to expand their boundaries consolidating low density fringe areas. Although we use spatial structure variables measured in the beginning year of the study period, these spatial variables may still be correlated with the residuals of the model if the growth patterns in the previous period remain the same in the 2000s. For this reason, we test the exogeneity of the spatial variables in OLS estimations using a Durbin-Wu-Hausman (DWH) test statistic (Baum, Schaffer, and Stillman, 2003).

We constructed an index of industrial churn, one of our dependent variables, for each metropolitan area, following Duranton (2007) and using the Regional Economic Information System (REIS) data spanning the years from 2001 to 2006. These data include the number employed at the level of 19 two-digit North American Industry Classification System (NAICS) sectors. As shown in equation (2), the churn index measures gross employment reallocation across industrial sectors in each metropolitan area c. This index computes every industry's employment change in each year in absolute terms normalized by total employment of the metropolitan area. Then, it adds up the normalized employment changes for all industries and years and divides by the number of years. Thus, this churn index presents an annual employment change normalized by metropolitan employment during the five-year period in the early 2000s. Between 2001 and 2006, the average of estimated churn index among 79 metropolitan areas was 3.81 percent. Our estimate is substantially smaller than the estimate by Duranton (2007), 8.26, because he used more disaggregated data (70 two-digit SIC sectors). But these are not available in the REIS data.

$$Churn_c = \frac{1}{5} \sum_{t=2001}^{2006} \sum_{z=1}^{19} \left| \frac{e_c(z,t+1) - e_c(z,t)}{e_c(t)} \right| \tag{2}$$

, where z = economic sector, t = year, e = employment, and c=MSA.

Another dependent variable used in our analysis, NNBF, presents the extent of entrepreneurial activities in metropolitan areas. This index can be defined in a fairly straightforward way as in equation (3) (Hobbs, Stansel, and Gohmann, 2008). The U.S. Small Business Administration provides business birth and death data and NNBF estimates based on the Statistics of U.S. Businesses collected by the U. S. Census Bureau. We used the average of NNBF indices for 6 years from 2000 to 2005 as a dependent variable.

$$NNBF = (\text{business births} - \text{business deaths}) / \text{total businesses} * 100 \quad (3)$$

The literature cited above suggests that metropolitan areas with more entrepreneurial activities and more new business formation would be more adept at successful churning of the industrial base and will ultimately experience greater economic growth. Thus, we expect that metropolitan growth, NNBF and measures of industrial churn will be highly correlated. Table 2 presents a correlation matrix of the three metropolitan performance indicators and two attributes of metropolitan areas. Both NNBF and the industrial churn index were highly correlated with employment growth, with correlation coefficients 0.754 and 0.573, respectively. Only industry turnover was statistically significantly correlated with metropolitan area employment size and population density. Larger and denser metros were less adept at industrial turnover in the early 2000s. We will revisit these variables' coefficients after controlling for other covariates in the next section on regression results.

***Table 2: Correlation matrix of key variables***

| | Log emp growth | Industrial churn | NNBF | Log emp size | Log pop density |
|---|---|---|---|---|---|
| Log emp growth | 1.000 | | | | |
| Industrial churn | 0.573 | 1.000 | | | |
| | (<.0001) | | | | |
| NNBF | 0.754 | 0.502 | 1.000 | | |
| | (<.0001) | (<.0001) | | | |
| Log emp size | -0.162 | -0.424 | 0.072 | 1.000 | |
| | (0.154) | (<.0001) | (0.529) | | |
| Log pop density[1] | -0.112 | -0.244 | 0.183 | 0.551 | 1.000 |
| | (0.324) | (0.031) | (0.107) | (<.0001) | |

1. Population density is measured for the core urbanized area of each metropolitan area.
* P-value in parentheses.

Most of explanatory variables are measured as of 2000 (or 2001) or as the average value for the period ending in 2000. These include log population density (for the core of the metro area only), industrial mix, local amenities, and human capital and other demographic variables. Table 3 defines and describes these variables. While population density has been suggested to have productivity effects by lowering transportation costs, and/or by promoting positive externalities and specialization (Ciccone and Hall, 1996), it trades off against higher congestion costs (Carlino and Chatterjee, 2002). It should be noted that population density is measured for the *core urbanized area in* each metro area because widely used metropolitan statistical area (MSA) boundaries are composed of counties and may misrepresent the functional economic areas.

Human capital accumulation is increasingly emphasized in urban economics and economic growth literature (Simon and Nardinelli, 2002; Glaeser and Shapiro, 2003; Simon, 2004; Shapiro, 2006). The percentage of college graduates, minorities, immigrants, and older population, and the poverty rate are obvious control variables. We expect that metropolitan areas with a more manufacturing-oriented industrial base would grow relatively slowly. For amenities, we control mean January temperature, annual precipitation, and violent crime rate variables that are generally location specific. However, price and wage variables are excluded from the model due to endogeneity issues.

Our main data sources are the 2000 Population Census, the 2000 Census Transportation Planning Package, and the Regional Economic Information System (REIS) 1969-2006 data published by the U.S. Bureau of Economic Analysis. Amenity variables came from the 2004 County and City Data Book and from the Uniform Crime Reports by the Federal Bureau of Investigation (FBI).

***Table 3: Definitions of variables***

| Variables | Descriptions |
|---|---|
| **Dependent variables** | |
| Industrial churn | Gross employment reallocation across sectors from 2001 to 2006 (equation 2) |
| NNBF | Average NNBF between 2000 and 2005 (equation 3) |
| Log employment growth | Log (2006 employment) – log (2001 employment) |
| **Metropolitan size and spatial structure** | |
| Log population | Log(2000 population) |
| Log employment | Log(2001 employment) |
| Log population density[1] | Log(2000 population/mile$^2$), measured for the core urbanized area |
| Dispersion | Percent dispersed location's share of metro employment (Column C in Table 2) |
| Polycentricity | Subcenters' share of center employment (the last column in table 2): subcenter' emp. / (subcenters' emp. + CBD emp.) * 100 |
| **Industrial mix** | |
| Percent manufacturing | Percent manufacturing's share of total metro employment in 2001 |
| **Human capital and demographic variables** | |
| Percent nonwhite | Percent nonwhite population 2000 |
| Percent immigrants | Percent foreign-born population 2000 |
| Percent pop over 64 | Percent population over 64 years 2000 |
| Percent college | Percent of 25+ years persons with bachelor's degree or higher 2000 |
| **Amenities** | |
| Mean Jan. temperature | January mean of average daily temperature (F°) for 1971-2000 |
| Annual precipitation | Average annual precipitation for 1971-2000 |
| Violent crime rate | Violent crimes known to police per 100,000 population, average for 1996-2000 |

1. Population density is measured for the core urbanized area of each metropolitan area.

Data sources: Employment data to calculate industrial churn, employment growth, and other employment related variables are drawn from Regional Economic Information System (REIS) 1969-2006 published by the Bureau of Economic Analysis, U.S. Department of Commerce; all population and socio-demographic data are from the 2000 Population Census; Amenity variables are from the 2004 County and City Data Book and from the Uniform Crime Reports by the Federal Bureau of Investigation (FBI).

## 3. QUANTIFYING SPATIAL STRUCTURE

The spatial structure of metropolitan areas is multidimensional and cannot be described by a single measure. And different urban form dimensions are associated with different geographical scales (Schwanen, 2003). While such variables as land use mix, street layouts, and micro-level accessibility are often used to quantify urban form at the neighborhood scale (Krizek, 2003; Srinivasan, 2002), the distinction between monocentric and polycentric structure has been recognized as a key spatial dimension at the metropolitan or urban area level (Clark, 2000). Urban economists recently called attention to yet another spatial dimension, urban dispersion or diffusion (Gordon and Richardson, 1996; Wheaton, 2004). Meanwhile, Galster and his colleagues (Galster et al., 2001; Cutsinger et al., 2005) expanded the list of metro-level spatial measures in an effort to develop measurements of urban sprawl, but some of their measures seem redundant.

We have chosen to quantify two dimensions of metropolitan level spatial structure, dispersion and polycentricity that have direct implications for economic efficiency and urban growth as discussed above. Dispersion measures the extent to which economic activities are spread out throughout the urban space outside major employment centers. Polycentricity represents the degree to which center functions are shared among multiple activity centers rather than being centralized in a single urban core, CBD. It has been well documented that modern metropolitan areas have transformed from a monocentric to a polycentric structure, often with a substantial extent of dispersion (Anas, Arnott, and Small, 1998; Clark, 2000; Lang, 2003; Wheaton, 2004).

The question is how to quantify these two spatial variables. One possible approach is to develop dispersion and polycentricity indices. Galster et al. (2001) provide multiple indices for each spatial dimension at the metropolitan level – for instance, coefficient of variation and delta index for concentration dimension. The European Spatial Planning Observation Network (ESPON) also developed a polycentricity index using the size and location of cities, and connectivity between cities on the scale of countries and regions. However, most of these indices, typically ranging from zero to one, are less intuitive because the units of these indices bear no direct scale.

We quantify our two spatial dimensions based on how metropolitan jobs are distributed among three different location types: the center, identifiable subcenters, and locations outside these employment centers. The dispersion variable is defined as non-centered employment's share of metropolitan employment which is dispersed outside the identifiable employment (sub)centers. Polycentricity is measured by comparing the relative strengths of a metro's core central business district (CBD) and multiple employment subcenters. More specifically, the polycentricity variable in this paper is defined as the ratio of employment in all subcenters combined for all centers' (CBD and subcenters) employment. Thus, identifying all employment centers in the sample of metropolitan areas is an essential step in constructing the two spatial variables.

Following the relatively recent urban economics and planning literature (Gordon, Richardson, and Wong, 1986; McDonald, 1987; Giuliano and Small, 1991; McMillen, 2001), we identify employment clusters with significant employment densities as urban centers. Various geographers have recently shown that spatial statistics such as the Moran's I or the Getis-Ord local G statistic can also be used to idenfity density peaks (Han, 2005; Griffith and Wong, 2007; Maoh and Kanaroglou, 2007). The value of these spatial statistics, however, in identifying urban centers needs to be further explored.

We used McMillen's (2001) geographically weighted regression (GWR) procedure with some modification to identify CBDs and subcenters in the 79 largest U.S. metropolitan areas with the population of a half-million and above in 2000. Because our employment centers identification procedure is explained in detail in our previous papers (Lee, 2007; Lee and Gordon, 2007), we provide only a brief description of the procedure and summary results here. A basic idea behind the centers identification procedure is to identify clusters of census tracts that have significantly higher employment density than surrounding zones. In the first step, we estimated two smoothed employment density surfaces using the GWR technique. The GWR is a spatial version of locally weighted regression (LOESS) which is a multivariate smoothing technique with local fitting (Cleveland, 1979; Cleveland and Devlin, 1988; Brunsdon, Fotheringham, and Charlton, 1996; Fotheringham, Brunsdon, and Charlton, 2002). In both the LOESS and GWR, a multivariate regression model is fit to a subset of the data at each data point which contains only observations that are close to the data point being estimated. Whereas the distance between data points in the LOESS is measured in terms of Euclidean distance in the space of explanatory variables, geographical distance is used in the GWR approach. Both the LOESS and GWR provide varying coefficients of explanatory variables across data points that capture local characteristics of the relationships between dependent and explanatory variables. Thus, the density surface predicted by the varying coefficients estimated by the GWR presents more local variation in employment density than the density surface predicted by the global coefficients estimated by the ordinary least squares (OLS) regression. The larger the size of subsample of nearby observations (window size) used for data fitting, the less varying are the coefficients and hence the smoother density surface one obtains.

In the second step, we compared two estimated employment density surfaces by GWR – one estimated with a larger window (100 neighboring census tracts) and the other with a smaller window (10 census tracts) – and identified those census tracts for which the differentials between the two GWR estimates are significant. These density peaks for which density estimates from a smaller window GWR are significantly higher than the estimates by a larger window GWR are *candidates* for inclusion as urban centers. Finally, we defined those candidates that have more than 10,000 jobs as metropolitan employment centers. We used census tract level employment data from the 2000 Census Transportation Planning Package (CTPP) in density estimation and employment centers identification.

Table 1 shows the number of subcenters and employment shares for three different location types, CBDs, subcenters, and dispersed locations. Average values for three different metropolitan population size groups and the data for each metropolitan area are presented for the largest metro group. One of the most outstanding spatial features of U.S. metropolis revealed in this table is that workplaces are predominantly dispersed outside employment centers. The average share of metropolitan jobs that are diffused outside CBDs and subcenters was about 80 percent in 2000. There was not much variation in the extent of dispersion versus clustering among metropolitan areas. The largest metro group showed only slightly more clustering than metropolitan areas in the smaller population-size group on average.

There was more variation in polycentricity. There was also a clear tendency for the larger metropolitan areas to be more polycentric with a greater number of subcenters and larger employment shares in subcenters than the smaller ones. Los Angeles was the most polycetric metropolis in the U.S. followed by San Francisco and Detroit. Nearly 30 percent of metropolitan jobs were shared among 53 subcenters, while the Los Angeles downtown accounted only for about three percent of metro area employment

These observations on polycentricy and dispersion among U.S. metropolitan areas suggest some theoretical implications. Any size of metropolitan area requires some center functions whose share of metropolitan employment varies moderately between about 15 and 30 percent. The subcenters' share of center functions tends to be bigger in large metropolitan areas that have more congestion while the majority of center functions are concentrated in the core CBD in small to medium size metropolitan areas. These findings are consistent with modern urban economic theories (Fujita and Ogawa, 1982; McMillen and Smith, 2003).

***Table 1: Employment shares by location type in U.S. metropolitan areas, 2000***

| Metro name | Population | Employment | No. of Subcenters | Share of emp (%) CBD (A) | Subcenters (B) | Dispersed (C) | Subcetners/ All Centers B/(A+B) |
|---|---|---|---|---|---|---|---|
| 3 million and plus average | | | 17.0 | 7.1 | 15.0 | 77.9 | 64.8 |
| New York | 21,200 | 9,418 | 33 | 9.9 | 11.2 | 78.8 | 53.0 |
| Los Angeles | 16,370 | 6,717 | 53 | 2.8 | 28.8 | 68.4 | 91.0 |
| Chicago | 9,158 | 4,248 | 17 | 7.0 | 11.9 | 81.1 | 62.9 |
| Washington | 7,608 | 3,815 | 16 | 7.4 | 11.8 | 80.8 | 61.3 |
| San Francisco | 7,039 | 3,513 | 22 | 5.9 | 24.2 | 70.0 | 80.5 |
| Philadelphia | 6,188 | 2,781 | 6 | 8.6 | 4.5 | 86.9 | 34.3 |
| Boston | 5,829 | 2,974 | 12 | 8.0 | 8.0 | 84.0 | 50.1 |
| Detroit | 5,456 | 2,509 | 22 | 5.2 | 22.2 | 72.6 | 81.1 |
| Dallas | 5,222 | 2,566 | 10 | 4.9 | 15.8 | 79.3 | 76.2 |
| Houston | 4,670 | 2,076 | 14 | 8.0 | 20.8 | 71.2 | 72.3 |
| Atlanta | 4,112 | 2,088 | 6 | 8.0 | 10.7 | 81.3 | 57.2 |
| Miami | 3,876 | 1,624 | 6 | 7.5 | 15.0 | 77.5 | 66.8 |
| Seattle | 3,555 | 1,745 | 7 | 9.3 | 11.9 | 78.8 | 56.0 |
| Phoenix | 3,252 | 1,464 | 9 | 7.1 | 12.9 | 79.9 | 64.4 |
| 1 to 3 million average | | | 2.6 | 10.8 | 7.0 | 82.2 | 38.3 |
| half to 1 million average | | | 0.9 | 12.2 | 5.2 | 82.6 | 25.7 |

## 4. ESTIMATION RESULTS

Tables 4 to 6 present estimation results from the OLS estimations for employment growth, NNBF, and industrial churn, respectively. As mentioned above, we tested the possible endogenity of spatial structure variables; the Durbin-Wu-Hausman (DWH) test statistics are presented for Models 2 and 3 in each table. Among the instrumental variables predicting spatial structure in estimating the DWH statistics were the congestion index by the Texas Transportation Institute (TTI), an indicator of coastal location, the number of municipalities per metro population, core central city's population share, and the number of years since the metro area population surpassed the half of 2000 population. The DWH test results indicate that the null hypothesis of exogeneity of spatial variables cannot be rejected in any of the estimations. Thus, we maintain the exogeneity assumptions and present the results of OLS estimations because OLS estimators are more efficient than instrumental variable (IV) estimators when the spatial variables can be assumed exogenous.

Our results show a better fit for employment growth than for the other two growth indicators. Table 4 showed the highest explanatory power with most of the control variables being significant with the expected signs. Employment size was positive and significant in three models where spatial variables were included. Average population density in the core urbanized area was also consistently significant with a negative sign, which is consistent with the long term deconcentration trend that Carlino and Chatterjee (2002) found. It may be that congestion costs dominated any positive externalities associated with density (Ciccone and Hall, 1996) in the years of the early 2000s. The coefficients of most other control variables except for the percentage college graduates are consistent with the results of our previous paper using the data for the 1990s. Large manufacturing's share and large non-white and older population had negative impacts on employment growth while percentage immigrants had positive impacts. Consistent with the previous literature cited, warmer and drier weather consistently contributed to employment growth. However, none of our spatial variables were significant in the OLS estimations.

Fewer control variables were found to be significant in the estimation for the NNBF and industrial churn models than in employment growth models. It should be noted that urban growth is more than simply entrepreneurial activities and industrial turnover although the latter influence the former in the long run. While the climate variables, manufacturing's share, and some of the demographic variables had consistent impacts on NNBF, metropolitan employment size, population density, and spatial structure did not have significant influence on NNBF in the early 2000s. In the industrial churn models, only two variables, employment size and mean January temperature were significant.

These OLS estimation results are not wholly consistent with our previous results for the 1990s (Lee and Gordon, 2007). The interaction variables of dispersion and metropolitan population (employment) size were found to be significant in both population and employment growth models in the 1990s, which suggests that more clustering in small metros and more dispersion in large metros were associated with faster employment growth. We suspect that the five-year period analyzed in this study may be too short to observe the links between spatial form and growth indicators. Further, the recession and the September 11$^{th}$ terrorist attacks in 2001 may have complicated the equation. However, we were constrained by data availability because the REIS data report local area statistics by NAICS only from 2001.

The LOESS estimations yielded results that are more consistent with the growth pattern in the 1990s. Figures 2 to 4 show varying coefficients of spatial variables, dispersion and polycentricity, against log employment size. The coefficients of polycentricity were close to zero across different metropolitan size in all three models. Subcenters' share of clustered employment was not a significant factor affecting employment growth and related indicators. It was the coefficients of employment dispersion that showed considerable variation across employment size. Consistent with our results for the 1990s, (repeated in Figures 5) employment dispersion had negative or zero effects on metropolitan performance for small metropolitan areas while it positively affected growth indicators in large metropolitan areas. These patterns are observed in all three models -- for employment growth, NNBF, and industrial churn.

***Table 4: OLS estimation results for employment growth***

| | Model 1 | | Model 2 | | Model 3 | | Model 4 | |
|---|---|---|---|---|---|---|---|---|
| | Beta | T | Beta | t | Beta | t | Beta | t |
| Dispersion | | | 0.0006 | 0.76 | | | 0.0002 | 0.18 |
| Polycentric | | | | | -0.0003 | -1.51 | -0.0003 | -1.19 |
| Dispersion * log emp. | | | 0.0012 | 1.40 | | | 0.0009 | 0.77 |
| Polycentric * log emp. | | | | | -0.0003 | -1.42 | -0.0001 | -0.46 |
| log employment | 0.0113 | 1.57 | 0.0126 | 1.73 * | 0.0190 | 2.27 ** | 0.0177 | 2.04 ** |
| log pop. Density | -0.1098 | -5.44 *** | -0.1067 | -5.18 *** | -0.1114 | -5.53 *** | -0.1090 | -5.18 *** |
| % manufacturing | -0.0060 | -5.21 *** | -0.0054 | -4.35 *** | -0.0053 | -4.44 *** | -0.0050 | -3.84 *** |
| % nonwhite | -0.0014 | -2.06 ** | -0.0013 | -1.84 * | -0.0012 | -1.64 | -0.0012 | -1.64 |
| % immigrants | 0.0015 | 1.72 * | 0.0017 | 1.96 * | 0.0017 | 2.00 * | 0.0018 | 2.03 ** |
| % pop over 64 | -0.0041 | -2.41 ** | -0.0041 | -2.43 ** | -0.0038 | -2.29 ** | -0.0040 | -2.32 ** |
| % pop college | -0.0022 | -2.15 ** | -0.0021 | -2.10 ** | -0.0022 | -2.17 ** | -0.0022 | -2.14 ** |
| mean Jan. temperature | 0.0020 | 3.76 *** | 0.0021 | 3.94 *** | 0.0021 | 4.02 *** | 0.0022 | 4.03 *** |
| annual precipitation | -0.0016 | -4.07 *** | -0.0016 | -4.16 *** | -0.0017 | -4.29 *** | -0.0017 | -4.20 *** |
| violent crime rate | 0.0000 | -0.02 | 0.0000 | -0.06 | 0.0000 | -0.12 | 0.0000 | -0.12 |
| Constant | 1.1146 | 6.45 *** | 1.0762 | 6.11 *** | 1.1104 | 6.46 *** | 1.0866 | 6.06 *** |
| R sq. | 0.679 | | 0.690 | | 0.694 | | 0.697 | |
| Adj. R sq. | 0.632 | | 0.634 | | 0.638 | | 0.630 | |
| DWH chi-sq test (df=1) | | | | 0.47 | | 0.98 | | |

1. The dependent variable of all models is log employment growth between 2001 and 2006.
2. The number of observations of all models is 79.
3. * Significant at 10%; ** significant at 5%; *** significant at 1%.

***Table 5: OLS estimation results for NNBF***

| | Model 1 | | Model 2 | | Model 3 | | Model 4 | |
|---|---|---|---|---|---|---|---|---|
| | Beta | T | Beta | T | Beta | t | Beta | t |
| Dispersion | | | -0.0023 | -0.17 | | | -0.0059 | -0.37 |
| Polycentric | | | | | -0.0026 | -0.66 | -0.0027 | -0.62 |
| Dispersion * log emp. | | | 0.0185 | 1.18 | | | 0.0237 | 1.07 |
| Polycentric * log emp. | | | | | -0.0025 | -0.63 | 0.0014 | 0.24 |
| log employment | 0.0426 | 0.32 | 0.0531 | 0.39 | 0.1051 | 0.67 | 0.0846 | 0.52 |
| log pop. Density | -0.2480 | -0.67 | -0.2623 | -0.69 | -0.2616 | -0.69 | -0.2521 | -0.64 |
| % manufacturing | -0.0801 | -3.8 *** | -0.0690 | -2.98 *** | -0.0746 | -3.33 *** | -0.0636 | -2.61 ** |
| % nonwhite | -0.0404 | -3.19 *** | -0.0395 | -3.08 *** | -0.0381 | -2.91 *** | -0.0391 | -2.97 *** |
| % immigrants | 0.0002 | 0.01 | 0.0061 | 0.37 | 0.0025 | 0.16 | 0.0061 | 0.37 |
| % pop over 64 | -0.0555 | -1.79 * | -0.0568 | -1.82 * | -0.0535 | -1.70 * | -0.0569 | -1.80 * |
| % pop college | 0.0228 | 1.22 | 0.0235 | 1.25 | 0.0228 | 1.21 | 0.0227 | 1.19 |
| mean Jan. temperature | 0.0447 | 4.59 *** | 0.0456 | 4.62 *** | 0.0460 | 4.60 *** | 0.0468 | 4.64 *** |
| annual precipitation | -0.0181 | -2.53 ** | -0.0188 | -2.61 ** | -0.0188 | -2.58 ** | -0.0188 | -2.55 ** |
| violent crime rate | 0.0003 | 0.78 | 0.0004 | 0.83 | 0.0003 | 0.73 | 0.0004 | 0.78 |
| Constant | 3.8568 | 1.21 | 3.7730 | 1.16 | 3.8246 | 1.19 | 3.6008 | 1.08 |
| R sq. | 0.593 | | 0.602 | | 0.597 | | 0.606 | |
| Adj. R sq. | 0.533 | | 0.529 | | 0.523 | | 0.520 | |
| DWH chi-sq test (df=1) | | | | 0.001 | | 1.385 | | |

1. The dependent variable of all models is the average NNBF for the period of 2000 - 2005.
2. The number of observations of all models is 79.
3. * Significant at 10%; ** significant at 5%; *** significant at 1%.

*Table 6: OLS estimation results for industrial churn*

| | Model 1 | | Model 2 | | Model 3 | | Model 4 | |
|---|---|---|---|---|---|---|---|---|
| | Beta | T | Beta | T | Beta | t | Beta | t |
| Dispersion | | | -0.0106 | -0.67 | | | -0.0180 | -1.02 |
| Polycentric | | | | | -0.0035 | -0.80 | -0.0052 | -1.07 |
| Dispersion * log emp. | | | 0.0093 | 0.53 | | | 0.0129 | 0.52 |
| Polycentric * log emp. | | | | | -0.0012 | -0.26 | 0.0004 | 0.06 |
| log employment | -0.4552 | -3.06 *** | -0.4577 | -3.03 *** | -0.3902 | -2.23 ** | -0.3824 | -2.12 ** |
| log pop. Density | -0.5550 | -1.34 | -0.6148 | -1.44 | -0.5481 | -1.30 | -0.6220 | -1.42 |
| % manufacturing | -0.0331 | -1.4 | -0.0252 | -0.97 | -0.0280 | -1.12 | -0.0160 | -0.59 |
| % nonwhite | -0.0144 | -1.02 | -0.0151 | -1.05 | -0.0124 | -0.85 | -0.0137 | -0.93 |
| % immigrants | 0.0176 | 1.02 | 0.0219 | 1.19 | 0.0183 | 1.01 | 0.0226 | 1.22 |
| % pop over 64 | 0.0278 | 0.8 | 0.0263 | 0.75 | 0.0296 | 0.84 | 0.0272 | 0.77 |
| % pop college | 0.0162 | 0.78 | 0.0163 | 0.77 | 0.0156 | 0.74 | 0.0149 | 0.70 |
| mean Jan. temperature | 0.0427 | 3.93 *** | 0.0425 | 3.83 *** | 0.0443 | 3.97 *** | 0.0444 | 3.94 *** |
| annual precipitation | 0.0009 | 0.11 | 0.0004 | 0.05 | 0.0005 | 0.06 | 0.0001 | 0.02 |
| violent crime rate | 0.0000 | 0.03 | 0.0001 | 0.12 | 0.0000 | -0.04 | 0.0000 | 0.06 |
| Constant | 6.2931 | 1.77 * | 6.6791 | 1.83 * | 6.1094 | 1.70 * | 6.5702 | 1.76 * |
| R sq. | 0.547 | | 0.553 | | 0.552 | | 0.562 | |
| Adj. R sq. | 0.481 | | 0.471 | | 0.470 | | 0.467 | |
| DWH chi-sq test (df=1) | | | | 2.585 | | 0.438 | | |

1. The dependent variable of all models is the average industrial churn index for the period of 2001-2006.
2. The number of observations of all models is 79.
3. * Significant at 10%; ** significant at 5%; *** significant at 1%.

***Figure 2: Varying coefficients of spatial variables from LOESS estimation for employment growth***

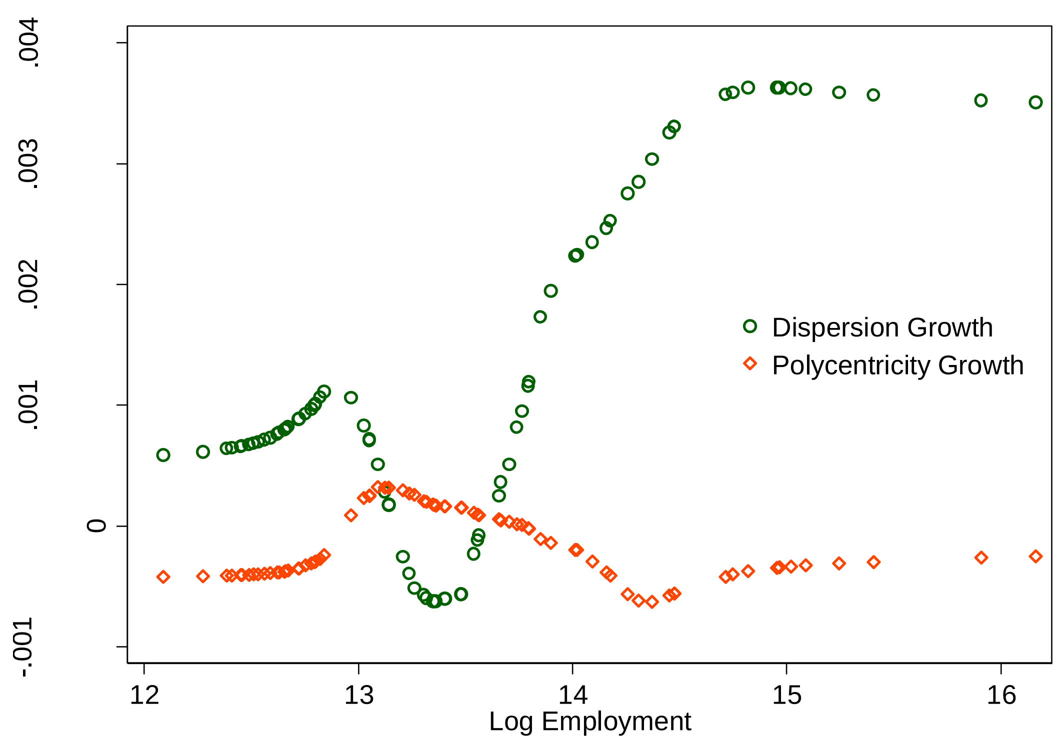


***Figure 3: Varying coefficients of spatial variables from LOESS estimation for NNBF***

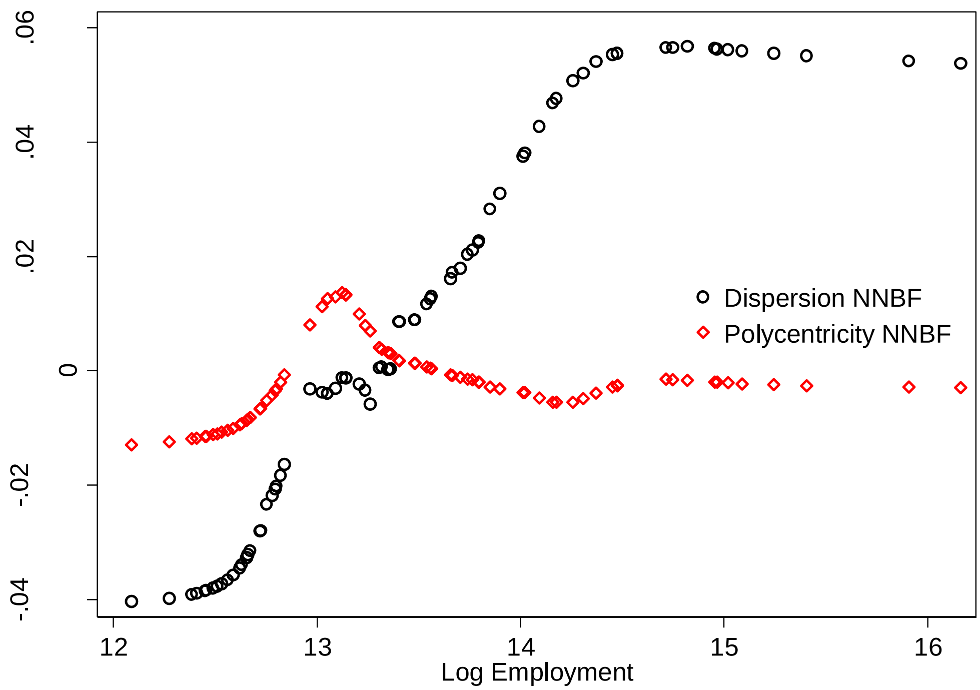



***Figure 4: Varying coefficients of spatial variables from LOESS estimation for industrial churn***

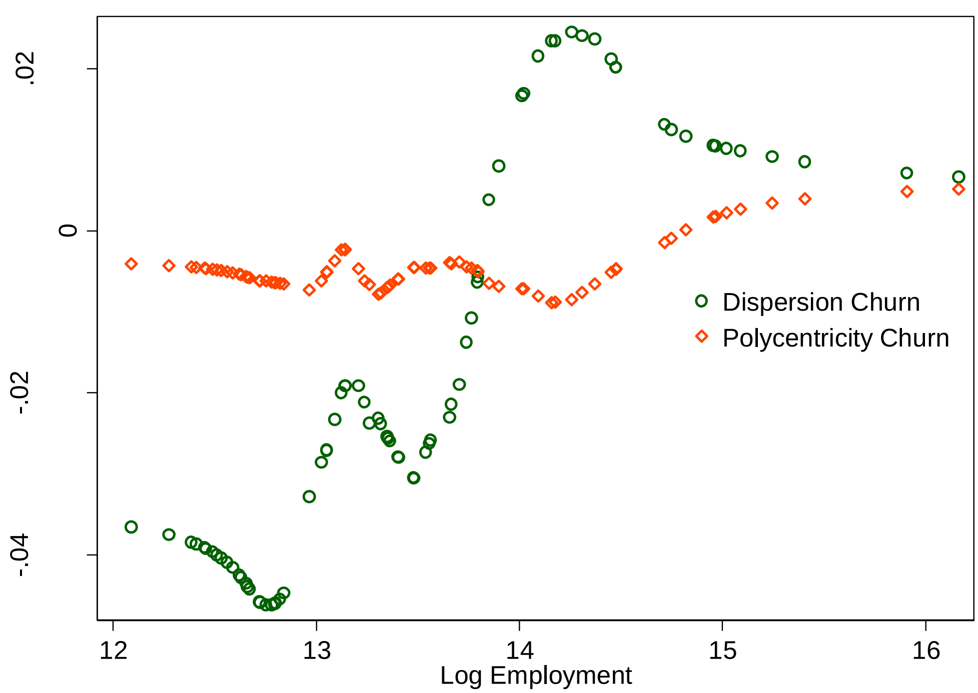
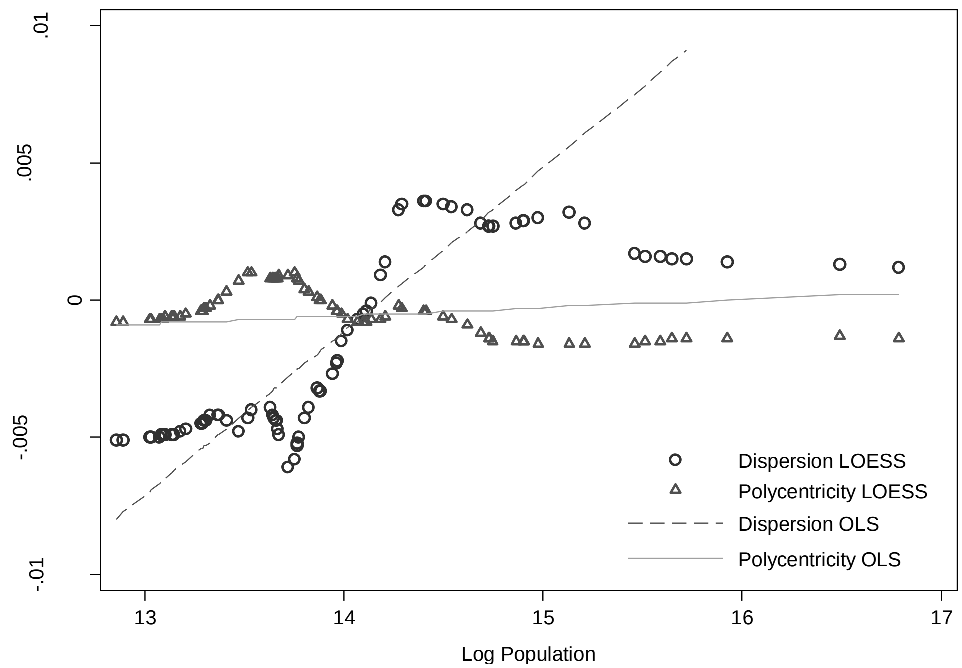


*Figure 5: Varying coefficients of spatial variables for employment growth in the 1990s*




The next question is whether or not the variation in estimated dispersion coefficients across employment sizes is statistically significant. Leung et al. (2000) developed a statistic with which one can test the nonstationarity of estimated coefficients. Estimated $F_3$ statistics (See Leung et al. 2000 for a detail estimation procedure) for each set of parameters for dispersion and polycentricity are shown in Table 7. For the set of polycentricity coefficients, we cannot reject the null hypothesis of the same coefficient across different metropolitan employment sizes at the 10 percent significant level. The variation in estimated dispersion coefficients – positive in large metro areas, but negative in small metro areas – was statistically significant at the 10 percent level only in NNBF model, but not in two other models.

*Table 7: Summary of LOESS statistics*

| | Employment growth model | NNBF model | Industrial churn model |
|---|---|---|---|
| Dispersion coefficient $F_3$ (2.92, 41.99) | 1.512 | 2.438* | 0.674 |
| α-value | 0.233 | 0.100 | 0.515 |
| Polycentricity coefficient $F_3$ (3.06, 41.99) | 1.068 | 1.668 | 0.195 |
| α-value | 0.373 | 0.189 | 0.899 |

* Significant at 10 percent.

## 5. CONCLUSIONS

In our previous paper, we showed evidence that links between metropolitan spatial structure and economic growth depend on metropolitan size. A metropolitan area with more clustered spatial form grew faster, perhaps enjoying agglomeration economies in small metropolitan areas; whereas more dispersion led to higher growth rates in large metropolitan areas in the 1990s. This follow-up study attempted to find similar patterns in entrepreneurial activities and industry turnover using the data for the early 2000s.

Spatial structure variables were not statistically significant in OLS estimations perhaps due to the choice of an inappropriate or too short study period. However, the coefficients of spatial variables estimated by the LOESS procedure showed similar patterns as in the previous study. The coefficients of employment dispersion were negative or close to zero for small metropolitan areas, but were positive in large metropolitan areas consistently in explaining employment growth, NNBF, and industrial churn. The variation in dispersion coefficients was statistically significant in the NNBF model. However, the coefficients of polycentriciy were close to zero across the board in all three models. Given the increasing interests among European planners in polycentric development, the results of this study have implications for the future research.

Characterizing the aspects of urban spatial structure that matter is not simple. Our work has been to tease some of the standard characteristics of settlement patterns out of the available secondary data. Where these were found to matter in simple growth models, they did so in ways that are plausible. We are encouraged by the results and plan further tests as more years of the REIS data become available. The efforts to further develop and elaborate measures of spatial structure are also warranted.

Cities grow and change and take on an increasingly important role as economies develop. Presumably, there is economic rhyme and reason to all this that can be uncovered by researchers. But there is also a large and growing literature that suggests that modern cities are a market failure. “Urban sprawl” is often used as a pejorative and “livable cities” summarizes a policy agenda geared to moderating long-standing suburbanization trends (Orski, 2009). While urban economists and others have discussed and tested the economic significance of metropolitan area average densities, one summary average over large metropolitan areas obscures important variations. There is much more to be learned about the variability of urban forms, how and why they evolve and how and why they are important. We have taken some small steps in this direction and expect that much more can be done.

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