Polycentric urban structure: The case of Milwaukee

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Introduction and summary

Theoretical models of urban structure are based on the assumption that all jobs are located in the central business district (CBD). Although this assumption was never literally true, it is a useful approximation for a traditional city in which the CBD holds the only large concentration of jobs. As metropolitan areas have become increasingly decentralized, traditional CBDs have come to account for a much smaller proportion of jobs than in the past. Large employment districts have arisen outside of central cities that rival the traditional city center as places of work. When these districts are large enough to have significant effects on urban spatial structure, they are referred to in the urban economics literature as "employment subcenters."

The distinction between a metropolitan area with multiple subcenters (or a polycentric urban structure) and one with much more dispersed suburban employment has important policy implications. Public transportation can be designed to serve subcenters. Buses can help alleviate severe congestion, and commuter rail lines may be able to serve large subcenters. Large subcenters may have enough jobs to warrant designing public transportation that brings central city workers to suburban job locations, which can help alleviate problems of a "spatial mismatch" between jobs and central city workers (Kain, 1968, and Ihlanfeldt and Sjoquist, 1990). The term "urban sprawl" appears to be used to describe an urban area whose residents have moved farther and farther from the central city, while driving past pockets of farmland and open space to get to their suburban jobs. Sprawl is likely to be less of a problem in an urban area whose suburban jobs are concentrated in subcenters. If jobs are confined to a relatively small number of suburban sites, workers will attempt to reduce their commuting costs by living nearby. This tendency toward suburban centralization is reinforced when transportation facilities are designed to serve the subcenters.

Spatial modeling of traditional monocentric cities is relatively easy because the site of the CBD is known in advance. Housing prices, land values, population density, and other variables of interest can be modeled as functions of distance to the CBD, with the addition of other variables of local importance, such as distance to Lake Michigan in Chicago or proximity to freeway interchanges and commuter train stations. In contrast, subcenter locations are not always obvious beforehand. The U.S. Census lists central places, which are generally older suburbs that once were satellite cities. However, subcenters are often relatively new developments (dubbed "edge cities" by Garreau, 1991) that may not have been incorporated as recently as 1960. Subcenter locations are an empirical issue: Does an area have enough employment that it has a significant local effect on variables such as employment density?

In this article, I critique various procedures for identifying employment subcenters and then use a procedure developed in McMillen (2002) to analyze subcenters in Milwaukee, Wisconsin. Milwaukee is interesting because it has not been the subject of a great deal of study, yet it is representative of older industrial cities that have maintained strong CBDs. I identify subcenters as local peaks in an estimated employment density function. I find that Milwaukee has one subcenter, which is located at the western edge of the city. It is notable for being the site of a Harley-Davidson manufacturing plant, although other

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firms also are located in the area. The subcenter has significant but highly localized effects on both employment and population densities in the Milwaukee area. Milwaukee remains a largely monocentric city.

Although Milwaukee has a monocentric spatial structure, it has ample suburban employment that is highly dispersed. Its single subcenter is readily accessible by central city residents, but the subcenter has fewer than 25,000 jobs in a metropolitan area of 821,158 workers. The dispersed nature of Milwaukee's suburban jobs makes it difficult to design a public transportation system that would help carry central city residents to suburban jobs. Milwaukee's dispersed employment increases the probability of central city unemployment and increases urban sprawl as suburban residents move still farther from the central city.

The rise of the polycentric city

The monocentric city model of Alonso (1964), Muth (1969), and Mills (1972) remains the most popular and influential model of urban spatial structure. The model depicts a stylized nineteenth century city, in which all jobs are located in the CBD. To reduce the cost of their daily commute, workers bid more for housing close to the city center. As a result, housing and land prices are predicted to fall with distance from the CBD. Spatial patterns for other variables of interest—population density, lot sizes, building heights, and the like—are all predicted to be simple functions of distance from the CBD.

Although these predictions have ample empirical support,[1] the central idea of the monocentric city model—that urban employment is concentrated in the traditional CBD—is no longer a suitable representation of urban spatial structure. Indeed, McDonald and McMillen's (1990) evidence of multiple peaks in land value functions in early twentieth-century Chicago suggests that the assumption of monocentricity was always more of a mathematical convenience than an accurate depiction of reality. Recent theoretical and empirical research in urban economics treats metropolitan areas as polycentric, that is, having multiple employment centers with varying degrees of influence on urban spatial patterns. Anas, Arnott, and Small (1998) present an excellent survey of theoretical and empirical models of polycentric cities.

The polycentric structure of urban areas has become more evident over time. Table 1 presents evidence of declining employment concentration in 11 midwestern urban areas. Across all 11 cities, 36.6 percent of suburban residents worked in the central city in 1960, whereas only 9.4 percent of city residents worked in the suburbs. The percentage of suburban residents working in the city ranged from 16.8 percent in Pittsburgh to 62.3 percent in Indianapolis. By 1990, the percentage of suburban residents working in the city had declined in every metropolitan area except Pittsburgh. Overall, only 28.4 percent of suburban residents worked in the central city in 1990, while 26.2 percent of city residents worked in the suburbs. Pittsburgh is an outlier because the large

TABLE 1

Journey to work patterns

	City residents working in the suburbs				Suburban residents working in the city			
	1960	1970	1980	1990	1960	1970	1980	1990
Buffalo	17.1	26.8	25.3	27.9	36.5	30.4	28.0	29.6
Chicago	6.6	16.1	18.4	22.5	34.6	27.1	22.5	25.6
Cincinnati	11.2	24.8	24.4	29.5	45.0	39.5	36.3	31.6
Cleveland	7.7	24.4	28.6	30.3	52.4	43.5	34.8	32.5
Columbus	7.8	19.1	17.7	24.2	50.6	54.5	48.1	49.7
Detroit	17.3	32.1	34.3	36.4	33.5	24.6	16.9	19.4
Indianapolis	6.1	18.5	9.8	12.1	62.3	44.8	48.7	48.9
Milwaukee	8.9	23.7	26.3	30.3	48.0	36.1	33.7	37.2
Minneapolis-St. Paul	6.6	19.7	24.5	29.8	52.1	43.5	31.2	30.5
Pittsburgh	11.2	19.1	20.1	21.4	16.8	24.6	26.4	24.3
St. Louis	8.3	21.1	24.0	35.9	36.7	30.0	25.4	27.9
All	9.4	21.2	21.8	26.2	36.6	31.8	27.0	28.4

Note: Data for 1990 reflect all central cities in the consolidated metropolitan statistical areas.
Source: U.S. Department of Commerce, Bureau of the Census, various years.

suburban steel plants closed during this period, leading to renewed employment centralization. Table 1 clearly shows that the CBD is not the dominant employment site in any of these cities, and that city residents are now nearly as likely to work in the suburbs as suburban residents are to work in the city.

The diminishing role of the CBD has come about despite the advantages it offers for firms wishing to locate in metropolitan areas. In-place public transportation, such as light rail, and radial boulevards and highways are designed to carry workers from outlying areas into the city. Reverse commuting and intrasuburban commuting is very difficult other than by automobile. Whereas highways lead from many directions in to the city, a suburban firm may find that its potential labor pool is limited to a relatively small geographic area around the workplace. In addition, theories of agglomeration such as Anas and Kim (1996), Berliant and Konishi (2000), and Fujita and Ogawa (1982) suggest that firms may enjoy significant cost advantages by locating near other firms. The close proximity of firms in the CBD facilitates face-to-face communication. Lawyers, bankers, and myriad consultants are all nearby in the CBD. Both suppliers and customers are likely to require only a short trip to visit a CBD firm.

But suburban locations offer different advantages. Land is significantly cheaper than in the CBD, and access to interstate highways is better and subject to less congestion. Large manufacturing firms are more likely to prefer suburban locations, as are distributors and wholesalers that have customers outside the metropolitan area. Suburban locations may reduce the wage bills of firms whose workers live in the suburbs because less compensation is needed for an expensive and time-consuming commute.

Employment subcenters combine many of the advantages of CBD and suburban locations. Highways and public transportation can serve subcenters much as they serve the CBD, bringing in an ample supply of workers from distant locations. Costs may be lower than in the CBD because land is cheaper and many workers like to live and work in the suburbs. Personal communication may be as easy as in the CBD when firms locate near one another in subcenters. Restaurants and other services find enough business to form concentrations in the vicinity. The diversity of business types may be lower than in the city, but large subcenters sometimes appear to mimic the diversity of CBDs while offering lower land and commuting costs. Large subcenters offer employment and shopping opportunities for which nearby residents are willing to pay a premium. As predicted by the monocentric city model for locations near the CBD, the rise in land values near subcenters leads to configurations with smaller lot sizes and higher population density that look like small cities.

Subcenter identification procedures

Empirical researchers have long recognized that cities are not truly monocentric. Variables representing distance from various employment sites other than the CBD are frequently included as explanatory variables in empirical studies of housing prices, employment density, and population density.[2] Sites that are significant enough to affect the overall urban spatial structure must be specified beforehand using this ad hoc approach. Forming the list of potential subcenters often draws on ample local knowledge, but may well be inconsistent with the data. Although statistically insignificant subcenter distance variables help indicate that the subcenter list is incorrect, they do not reveal subcenter sites that are omitted from the regressions.

The first formal procedure for identifying employment subcenters was proposed by McDonald (1987). He begins by estimating a simple employment density function for a standard monocentric city: $\log y_i = \alpha + \beta x_i + \varepsilon_i$, where y_i represents the number of employees per acre and x_i is distance from the CBD. Subcenters produce clusters of positive residuals in the estimated function. McDonald inspects the list of statistically significant positive residuals, and finds that O'Hare Airport is the dominant subcenter in the Chicago metropolitan area.

McDonald's novel approach poses several problems in practice. The notion of a "cluster" is subject to interpretation. Are two significant positive residuals among ten observations in a two-mile radius a cluster? A reasonable change in either the radius or the requisite number of positive residuals can potentially change the results dramatically. The procedure also suffers from statistical problems. The results are sensitive to the unit of analysis. Using extremely large tracts, McDonald (1987) finds a single subcenter in the Chicago area near O'Hare Airport. In a follow-up paper using square mile tracts, McDonald and Prather (1994) find additional subcenters in Schaumburg and central DuPage County. The local rise in employment density produced by a subcenter tends to flatten the estimated employment density function, which reduces the probability of identifying subcenters. Although the monocentric employment density function implies that gradients do not vary across the urban area, multiple subcenters or distinctive topographical features may lead to variations in gradients. Such functional form misspecification can hide potential subcenters.

Giuliano and Small (1991) propose another influential subcenter identification procedure. It has been employed in subsequent work by Bogart and Hwang (1999), Cervero and Wu (1997, 1998), and Small and Song (1994). Defining a subcenter as a set of contiguous tracts that have a minimum employment density of 10 employees per acre each and, together, have at least 10,000 employees, Giuliano and Small identify 32 subcenters in the Los Angeles area. This reasonable subcenter definition is sensitive to the cutoff points used for minimum employment density and total subcenter employment. The same cutoff points imply an unreasonably large subcenter in the northern Chicago suburbs with over 400,000 employees, leading McMillen and McDonald (1998) to raise the cutoffs to 20 employees per acre and 20,000 total employees. Local knowledge must guide the choice of cutoff points, limiting the analysis to familiar metropolitan areas.

Giuliano and Small's procedure is also sensitive to the unit of analysis. Their data set includes 1,146 tracts covering an area of 3,536 miles. In contrast, McMillen and McDonald's Chicago data set has 14,290 tracts in an area of 3,572 square miles. Data sets with small tracts are more likely to have pockets with low employment density, which reduces the number of subcenters identified using the Giuliano and Small procedure. This observation led McMillen and McDonald (1998) to work with proximity instead of contiguity: Two tracts are proximate to one another if they are within 1.5 miles. The number of subcenters is again sensitive to the definition of proximity.

Giuliano and Small define a subcenter as an area with large employment, with the definition of "large"—the cutoff points—being up to the analyst. Subsequent statistical analysis determines whether the subcenters have significant effects on such variables as employment density, population density, and housing prices. The cutoffs do not vary over the data set, which means that the minimum subcenter size is the same near the CBD as in distant suburbs. This characteristic of their procedure is not desirable if a subcenter is defined as an area with larger employment density than surrounding areas. Since densities tend to decrease with distance to the CBD, the minimum cutoffs should tend to decrease also. Then the question becomes how to vary the cutoffs.

Craig and Ng (2001) propose a procedure that eliminates many of the problems with the earlier methods. They use a nonparametric estimation procedure to obtain smoothed employment density estimates for Houston. Using a quantile regression approach, they focus on the 95th percentile of the employment density distribution. The quantile regression approach is attractive in this context because a subcenter is defined using the extremes of the distribution. Craig and Ng's estimated density function is symmetric about the CBD because they only use distance from the CBD as an explanatory variable for the estimates. They first look for local rises in the density–CBD relationship, and then inspect the rings to find sites with unusually high density and employment. They use their knowledge of Houston to accept or reject high-density sites as subcenters.

Craig and Ng's procedure is not as sensitive to the unit of analysis as the McDonald and Giuliano–Small procedures. Though larger tracts lead to smoother employment density functions, a large subcenter will produce a rise in the function whether the data set includes acres, quarter sections, or square miles. The procedure is readily reproducible by other researchers and requires scant knowledge of the local area. Much of the arbitrariness of the Giuliano–Small procedure is eliminated because the local rise that defines a subcenter is subject to tests of statistical significance. However, the Craig–Ng procedure requires some local knowledge to choose which sites are subcenters within rings around the CBD, and the imposition of symmetry around the CBD is unsuited to cities that are distinctly asymmetric due to varied terrain or multiple subcenters.

A nonparametric subcenter identification procedure

Nonparametric approaches offer significant advantages over simple linear regression procedures. Nonparametric estimators are flexible, allowing the slope of density functions to vary across the metropolitan area. As an example, suppose that employment density declines more rapidly on the north side of the city than on the south. The standard linear regression estimator used by McDonald (1987) imposes the same gradient on both sides of the city, which tends to produce positive residuals on the north side and negative residuals to the south. This functional form misspecification increases the probability of finding a subcenter on the north side of the city even if none exists. Craig and Ng's (2001) estimator is more flexible than standard linear regression, but does not avoid this type of misspecification because it imposes symmetry about the CBD. In contrast, nonparametric estimation procedures are sufficiently flexible to detect the difference in gradients across the two sides of the city.

McMillen (2002) proposes a nonparametric procedure for identifying subcenters in a variety of cities, including those with which the analyst is largely unfamiliar. It is a two-stage procedure that combines features of both the McDonald (1987) and Craig and Ng (2001) approaches. As in McDonald (1987), the first stage of the procedure identifies subcenter candidates through an analysis of the residuals of a smoothed employment density function. The procedure differs in that McMillen uses a nonparametric estimator, locally weighted regression, to estimate the employment density function.[3] The estimation procedure involves multiple applications of locally weighted regression. McMillen estimates a separate regression for locations for which a log-employment density estimate is desired. Observations closer to the target location receive more weight in the regressions. McMillen (2002) identifies subcenter candidates as significant residuals (at the 5 percent level) from the first-stage locally weighted log-density estimates. When significant residuals cluster together, he narrows the list of subcenter candidate sites to those with the highest predicted log-employment density among all observations with significant positive residuals in a three-mile radius.

The second stage of the procedure uses a *semiparametric* procedure (Robinson, 1988) to assess the significance of the potential subcenter sites in explaining employment density. The nonparametric part of the regression controls in a general way for the nuisance variable, *DCBD*, which is an acronym for *distance from the central business district*. Following Gallant (1981, 1983, and 1987), McMillen (2002) uses a flexible Fourier form to approximate the nonparametric part of the regression (see box 1). Distances to potential subcenter sites are included as explanatory variables in the parametric part of the regression. If the regression indicates that densities fall significantly with distance from a potential subcenter site, then the site is included in the final list of subcenters.

This procedure reflects the definition of subcenters listed earlier: Subcenters are sites that cause a significant local rise in log-employment densities, after controlling for distance from the CBD. Unlike Giuliano and Small (1991), McMillen (2002) uses statistical tests to determine the significance of subcenter sites. This feature makes it possible to apply the procedure for a variety of cities, including unfamiliar ones. Basing the procedure on a semiparametric regression analysis allows the analyst to conduct statistical tests of significance, while reducing the sensitivity of the analysis to restrictive functional form specifications, the size of the unit of observation, and the specification of arbitrary cutoff points.

Data

The data come from the Urban Element of the Census Transportation Planning Package, which is produced by the Department of Transportation's Bureau of Transportation Statistics (BTS). The BTS produced special tabulations of 1990 U.S. census data to match standard census data with their unit of analysis, which they term the *transportation analysis zone*, or "taz." The zones vary in size across metropolitan areas, but are usually smaller than census tracts or zip codes. All data for this study cover the Milwaukee metropolitan area, which comprises Milwaukee, Kenosha, Ozaukee, Racine, Washington, and Waukesha counties.[4]

The taz sizes average 2.1 square miles in this sample of 1,206 observations. Total population is 1,805,245, and total employment is 821,158, or 45.5 percent of the population. Average densities imply that population is more dispersed than employment. Employment density averages 2,598 workers per square mile, or 4.1 employees per acre. In contrast, population density averages 3,244 people per square mile, or 5.1 people per acre.

The Milwaukee subcenter

Figure 1 presents a map showing employment densities in the Milwaukee area. Aside from pockets of high densities in Racine and Kenosha, the map suggests that Milwaukee is not far from a stylized monocentric city. This finding is reflected in the McMillen (2002) procedure, which identifies a single employment

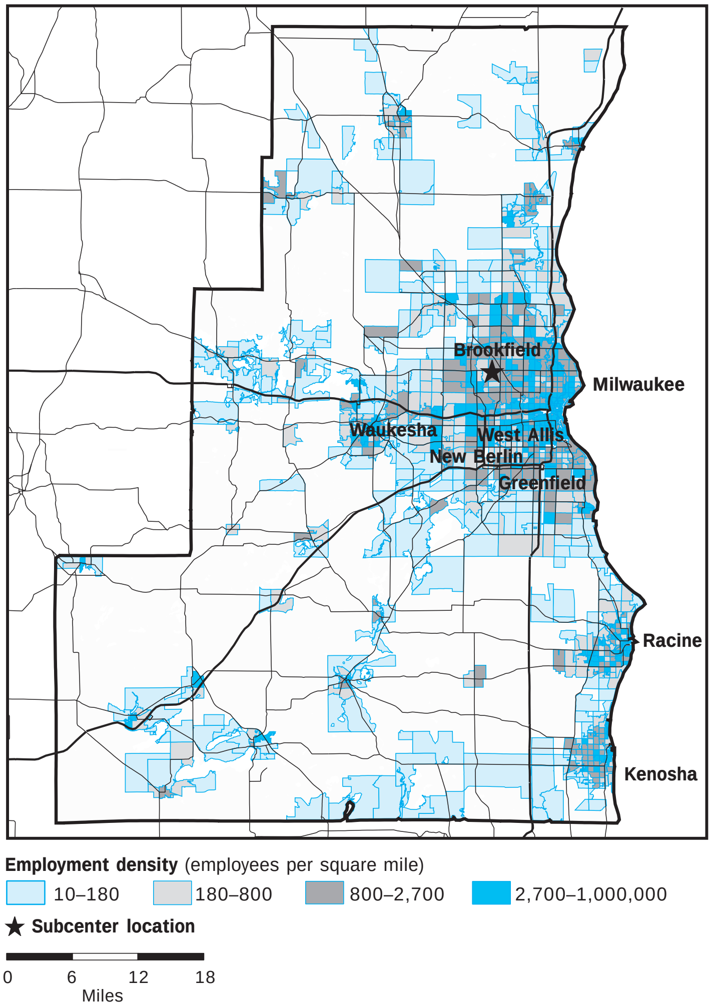
BOX 1

Fourier terms

The Fourier expansion uses sine and cosine terms to approximate the general function $g(DCBD)$. To implement the procedure, the variable *DCBD* is first transformed to lie between 0 and 2π, with the transformed variable denoted by z. The Fourier expansion is $g(DCBD_i) \approx \lambda_0 + \lambda_1 z_i + \lambda_2 z_i^2 + \Sigma_q(\gamma_q \cos(qz_i) + \delta_q \sin(qz_i))$, where $q = 1, \ldots, Q$. The Schwarz (1978) information criterion is used to choose the expansion length, Q. The optimal Q is the value that minimizes $S(m) = \log(s^2) + m\log(n)/n$, where m is the number of estimated coefficients ($m = 3 + 2Q$), s^2 is the estimated variance of the errors from the semiparametric regression, and n is the number of observations. Larger values of Q reduce the estimated variance but increase the second term. The subcenter distance variables are omitted when choosing Q.

FIGURE 1

Employment density in Milwaukee and subcenter location



Source: Author's calculations based on data from the U.S. Department of Commerce, Bureau of the Census, transportation planning package.

subcenter. Its location is shown in figure 1. The subcenter is at the edge of the City of Milwaukee, at the intersection of State Highway 45 and Route 190, near Wauwatosa. The site includes the main Harley-Davidson manufacturing plant. It meets the Giuliano and Small (1991) criterion for a subcenter by including two tracts with more than 10 employees per acre. The larger tract, which includes the Harley-Davidson plant, has 17.0 employees per acre and 10,344 total workers. The other tract has 10.5 employees per acre and 3,759 workers.

Table 2 provides more information on employment patterns in the Milwaukee area. The CBD is defined as an area one mile in diameter around the tract at the city center with the largest employment density. The subcenter is an area three miles in diameter around its midpoint. Both areas include 11 observations. Only 6.7 percent of Milwaukee's employment is in the CBD (as defined here), but the CBD is nonetheless more than twice as large as the subcenter, which has 3.0 percent of total employment in the metropolitan area. As predicted by urban theory, median earnings are highest in the CBD, but it is interesting to note that earnings on average are higher in the subcenter than in the rest of the city. The earnings differences are not large, but they suggest that either marginal productivity is higher in sites with high employment density or that firms must compensate workers for longer commutes. In keeping with the spatial mismatch hypothesis, African-Americans comprise a larger percentage of total employment in the CBD. In contrast to the spatial mismatch hypothesis, however, this tendency toward CBD employment may *increase* the average earnings of African-Americans because average earnings are lower elsewhere. In part because the subcenter is only 8.1 miles from the CBD, the percentage of African-Americans in the subcenter is closer to that in the CBD than in the rest of the city. This result is significant because it indicates that the commute to a nearby subcenter may be only slightly more burdensome than a commute to the CBD for central city residents.

Table 2 shows the employment mix in the CBD, subcenter, and the rest of the city for five traditional industry categories. The CBD specializes in the financial, insurance, and real estate sector (26.61 percent of CBD employment) and service industries (34.27 percent of CBD employment). In contrast, a larger percentage of the subcenter's employment (30.48 percent) is engaged in manufacturing, with a significant concentration in retail also. Service industries are underrepresented in the subcenter compared with the CBD or the rest of the city. On the whole, the employment mix in the subcenter is closer to the mix in the rest of the city than to the CBD.

Comparison of employment density estimates

Figure 2 presents graphs of the estimated log-employment densities along a ray from the CBD to the subcenter. The grey line shows that the initial

TABLE 2			
Employment mix			
	CBD	**Subcenter**	**Rest of city**
Total employment	54,669	24,967	741,522
Number of residents	4,508	19,260	1,781,477
Median earnings ($)	21,397	20,715	19,064
	(- - - - - - - % of total employment- - - - - - -)		
White	87.06	89.29	89.60
Black	9.75	9.05	7.82
Manufacturing	10.92	30.48	26.13
Transportation, communications, utilities, and wholesale	11.08	10.85	10.57
Retail	8.79	23.48	17.03
Financial, insurance, and real estate	26.61	9.99	5.56
Services	34.27	21.95	31.91

Note: CBD is central business district.
Source: Author's calculations based on data from the U.S. Department of Commerce, Bureau of the Census, transportation planning package.

locally weighted regression estimates decline rapidly with distance from the CBD up to about 18 miles, after which the decline is nearly linear. The black line shows that the simple exponential function used by McDonald (1987) is badly misspecified here, indicating a much less rapid rate of decline in densities after about seven miles than found using the more flexible nonparametric estimator. The Fourier estimates detect a sharp rise in employment density around the subcenter, although they too tend to overestimate densities in distant locations. Figure 2 shows that McDonald's estimator would have trouble finding subcenters in distant areas because the overestimate of densities will tend to produce *negative* rather than positive residuals.

Just as simple exponential function overestimates densities along the ray between the CBD and the subcenter, figure 3 shows that it tends to underestimate densities along a ray due south from the CBD. Densities do not decline as rapidly on the south side of Milwaukee as to the north. Together, figures 2 and 3 show the advantages of locally weighted regression's flexibility over the symmetric McDonald (1987) and Craig–Ng (2001) estimators.[5] Figure 4 shows an advantage of the nonparametric approach over the Giuliano–Small (1991) procedure. The entire log-employment density function lies below the cutoff point of 10 employees per acre, which is why only two tracts—those with large positive residuals—meet the cutoff. If the cutoff were raised to 20 employees per acre, the Giuliano–Small procedure would miss the subcenter entirely. If the cutoff point were lowered too far, the subcenter would simply be part of the CBD, or it would be so large as to be meaningless (as found in McMillen and McDonald, 1998, for Chicago).

FIGURE 2

Estimated employment density functions—ray between CBD and subcenter

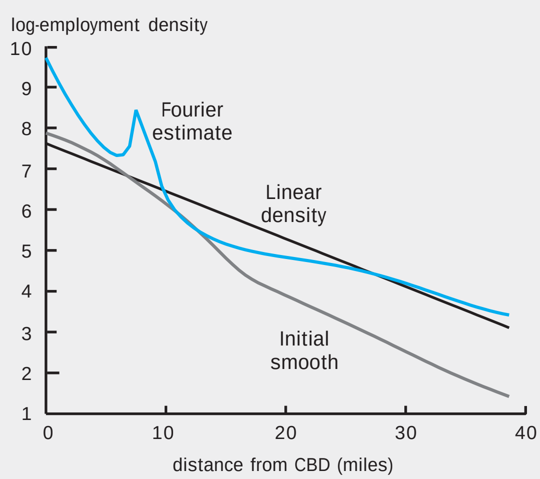


FIGURE 3

Estimated employment density functions—ray from CBD to south

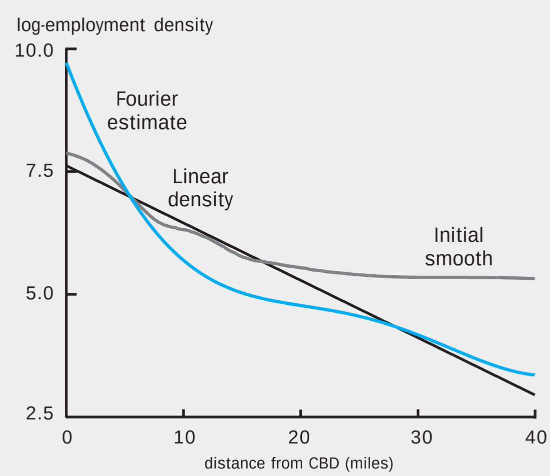
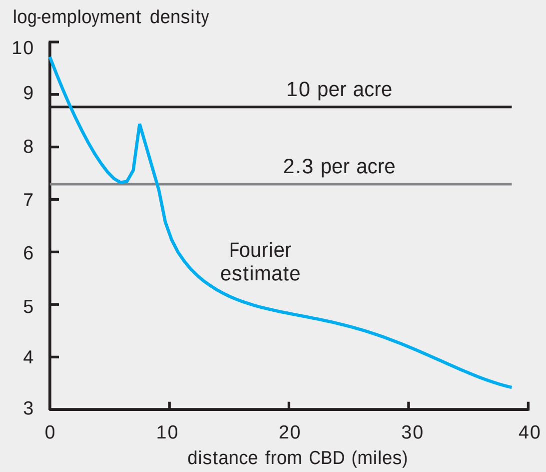


FIGURE 4

Cutoff points for Giuliano–Small method



Subcenters and urban sprawl

I define subcenters here as sites that cause significant *local* rises in employment densities. A question arises as to the extent of the subcenter's influence on the *overall* urban spatial structure. Traditionally in urban economics, urban decentralization is measured by the CBD gradient, which is the slope coefficient from a regression of the natural logarithm of population density on distance from the CBD (Clark, 1951; Macauley, 1985; McDonald, 1989; McDonald and Bowman, 1976; Mills, 1972; and Mills and Tan, 1980). The gradient measures the percentage decline in densities associated with a movement of one mile from the CBD. The relatively slow decline of densities in decentralized metropolitan areas is reflected in small gradients. Density gradients are thus a useful measure of urban sprawl.

The first column of results in table 3 presents the average gradients from various specifications of employment and population density functions. In a simple regression of log density on *DCBD*, employment density is estimated to decline by 11.7 percent and population density is estimated to decline by 7.6 percent with each mile from the CBD. These figures are consistent with those found previously for relatively centralized cities (for example, Macauley, 1985; or Mills and Tan, 1980). However, the apparent centralization of Milwaukee becomes more pronounced when more flexible functional forms are used in estimation. Flexible Fourier functions of *DCBD* imply much larger gradients: 28.2 percent per mile for employment density and 17.7 percent per mile for population density. Such steep declines in densities with distance to the CBD indicate a centralized urban area.

Milwaukee's subcenter has only a marginal impact on the estimated gradients. The gradients for distance from the CBD are virtually unchanged when the inverse of distance from the subcenter is added as an explanatory variable in the density regressions. For example, the employment density gradient only falls from –11.7 percent to –11.2 percent when the variable is added to a regression of log-employment density on *DCBD*. The second column of results in table 3 presents the corresponding gradients for distance from the subcenter, estimated using the same regressions as for the CBD gradients. The gradients, which are averages over the entire metropolitan area, are not statistically significant. Together, these results suggest that the subcenter has only a local effect on Milwaukee's spatial structure. It raises densities enough to have a statistically significant effect in the estimated functions, but not enough to be significant across the full metropolitan area or to cause severe bias in the estimated CBD gradients when omitted from the density functions.

The last column of table 3 presents the results of Lagrange multiplier (LM) tests for spatial autocorrelation (Anselin, 1988; Anselin et al., 1996; and Burridge, 1980). Spatial autocorrelation will be present if the residuals of the estimated density functions are correlated over space. If firms tend to cluster together, then the residuals of the employment density functions will be positively correlated spatially. The LM tests are thus a useful measure of spatial clustering. They are complementary to but different from our definition of a subcenter. Whereas a subcenter is an area with extremely high density, spatial autocorrelation may be found in areas without sharp peaks in density, yet with more clustering of employment than would be implied by random variation. Just as a metropolitan area with subcenters is less decentralized than an otherwise identical city with randomly distributed suburban employment, an area with a high degree of spatial autocorrelation in employment density is more centralized than an area with random variation in densities.

The LM tests presented in table 3 are highly significant in every case.[6] For the simple models in which only *DCBD* is included as an explanatory variable, the LM test statistics are 1,486.27 for employment density and 1,616.90 for population density. These values are far greater than the critical value of 3.84, and indicate an extremely high degree of spatial clustering of the residuals. The test statistics fall to 859.17 and 536.31 when the inverse of distance to the subcenter is added to the regressions. The decrease in the test statistics suggests that the residuals are

TABLE 3

Employment and population density

Explanatory variables	CBD gradient	Subcenter gradient	Spatial auto-correlation LM test
	Log-employment density		
Distance from CBD	–0.117 (0.006)		1,486.27
Fourier terms	–0.282 (0.073)		602.39
Distance from CBD and inverse of distance to subcenter	–0.112 (0.006)	–0.021 (0.020)	859.17
Fourier terms and inverse of distance to subcenter	–0.295 (0.074)	–0.033 (0.019)	592.13
	Log-population density		
Distance from CBD	–0.076 (0.004)		1,616.90
Fourier terms	–0.177 (0.037)		327.39
Distance from CBD and inverse of distance to subcenter	–0.074 (0.004)	–0.009 (0.009)	536.31
Fourier terms and inverse of distance to subcenter	–0.182 (0.037)	–0.013 (0.008)	321.20

Notes: The Fourier terms include z, z^2, cos(z), and sin(z), where z denotes the distance from the CBD multiplied by $2\pi/50$. See box 1, p. 19, for complete details on Fourier terms. Heteroscedasticity consistent standard errors (White, 1980) are in parentheses.

Source: Author's calculations based on data from the U.S. Department of Commerce, Bureau of the Census, transportation planning package.

much less clustered after allowing densities to rise near the subcenter. The higher degree of clustering in the model without the subcenter distance variable is a direct result of a large number of positive residuals near the subcenter site. Adding the Fourier expansion terms—z, z^2, cos(z), and sin(z)—leads to further reductions in the LM test statistics. In the most general models, which include both the Fourier expansion terms and the inverse of distance to the subcenter, the LM test statistics are 592.13 for employment density and 321.20 for population density. Thus, the LM tests suggest that spatial autocorrelation remains significant even after controlling for the effects of the subcenter and when using a very general functional form for *DCBD*. Whereas estimated density functions imply that densities decline smoothly with distances from the CBD and subcenter, the spatial autocorrelation tests suggest that densities are in fact much more highly clustered than implied by smooth functions of distance.

Overall, these results indicate that Milwaukee remains a centralized city, although it has many suburban jobs. Even simple exponential functions imply large gradients for both employment and population density. More flexible functional forms imply still steeper gradients. Both employment and population are spread across Milwaukee in clusters, with densities that decline rapidly with distance from the city center.

Conclusion

Milwaukee's CBD still dominates metropolitan-wide employment and population density patterns. Nevertheless, jobs are spread throughout the metropolitan area. Table 1 shows that a majority of Milwaukee's suburban residents worked in the suburbs in 1990, and over 30 percent of its central city residents also worked in the suburbs. One area at the edge of the city is large enough to qualify for subcenter status. It is the location for a Harley-Davidson manufacturing plant and is the site for more than 20,000 jobs. The subcenter has significant effects on employment density and population density patterns in the vicinity. However, the effects are highly localized. Milwaukee is still primarily a monocentric city. Although it has ample suburban employment, the CBD dominates overall spatial density patterns in a manner largely consistent with Brueckner's (1979) version of the monocentric city model.

With only one subcenter set in the midst of ample suburban employment, little can be done in Milwaukee to relieve problems associated with congestion and a spatial mismatch between jobs and workers. If firms in the Milwaukee area had moved to a few large suburban subcenters, public transportation could be designed to carry commuters efficiently to suburban jobs. Central-city residents would not be at a serious disadvantage in taking suburban jobs if they could easily take buses to the large subcenters. Milwaukee's single subcenter can indeed be reached easily by central-city residents. However, the majority of Milwaukee's jobs are now scattered across the metropolitan area. This spatial pattern of employment opportunities makes it difficult for central-city residents to find jobs, and increases the probability that suburbanites will move still farther from the city center.

Researchers have identified subcenters for only a small number of cities—Chicago, Cleveland, Dallas, Houston, Los Angeles, New Orleans, the San

Francisco Bay Area, and now Milwaukee. It remains an open question whether there are systematic patterns across metropolitan areas concerning subcenters. Is there a critical population level at which subcenters become more likely? Are subcenters more likely in old or new cities or in cities with good public transportation service or those that rely predominantly on the automobile? Do subcenters increase the probability of reverse commuting and the probability of central city unemployment? Do subcenters increase the degree of sprawl by allowing suburbanites to live still farther from the center of the city? Do subcenters tend to specialize in particular types of employment, such as manufacturing or financial services? Recently developed procedures for identifying subcenters make it possible for researchers to answer these questions after determining the number, size, and employment mix of subcenters across metropolitan areas.

NOTES

[1]Examples include Clark (1951), Fales and Moses (1972), Macauley (1985), McDonald (1989), McDonald and Bowman (1976; 1979), McMillen (1996), and Mills (1969; 1970).

[2]Examples include Bender and Hwang (1985), Dowall and Treffeisen (1991), Gordon et al. (1986), Greene (1980), Griffith (1981), Heikkila et al. (1989), Richardson et al. (1990), and Shukla and Waddell (1991).

[3]Stone (1977) and Cleveland (1979) first proposed the locally weighted regression procedure, which has since been extended by Cleveland and Devlin (1988), Fan (1992, 1993), Fan and Gijbels (1992), and Ruppert and Wand (1994). It is a simple extension of the kernel regression estimator. Locally weighted regression has been used extensively in spatial modeling. Examples include Brunsdon et al. (1996), McMillen and McDonald (1997), McMillen (2002), Meese and Wallace (1991), Pavlov (2000), and Yuming and Somerville (2001).

[4]I used a mapping program to measure the area of each taz (in square miles) and to provide coordinates for the taz center points. These coordinates are used to measure distance to the CBD.

[5]As employed here, the Fourier estimator also imposes symmetry about the CBD. This misspecification is less critical in the second stage of the analysis, where the objective is only to assess the statistical significance of the subcenters. The misspecification could be eliminated by estimating $g(x_1,x_2)$ nonparametrically rather than $g(DCBD)$, where x_1 and x_2 represent distances north and east of the CBD.

[6]The test statistic is $(e'We/s^2)^2/\mathrm{tr}(W'W + WW)$, where e is the vector of residuals and s^2 is the estimated variance of the regression. W is a "spatial contiguity matrix," representing the spatial relationship between observations. For the models in table 3, $W_{ij} = 1$ when observation j is among the nearest 1 percent of the observations to observation i, and $W_{ij} = 0$ otherwise. The rows of the $n \times n$ matrix W are then normalized such that each sums to one. The test statistic is distributed χ^2 with one degree of freedom, which implies a critical value of 3.84 for a test with a 5 percent significance level.

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