How many? Using ESDA to evaluate polycentricity in the US cities

Daniel Arribas-Bel*

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Abstract

For decades, the analysis of urban structures and, particularly, of the existence and relevance of centers and subcenters of employment density in urban areas has been focus of study of many economists. However, there is no common agreement on how these phenomena should be identified and quantified in reality. This paper tries to contribute to the latter by suggesting an algorithm based on the use of local indicators of spatial association (LISA) to identify centers and subcenters in an urban area with no requirement of local knowledge. The procedure is then applied to the US metropolitan statistical areas finding that more than three quarters of the cities still show monocentric structures.

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Keywords Urban spatial structure, polycentricity, employment center identification, ESDA (exploratory spatial data analysis).

*Department of Economic Analysis, University of Zaragoza. Gran Vía, 2, 50005, Zaragoza (SPAIN). Contact mail: darribas@unizar.es. The author especially thanks for the fruitful comments and interaction provided to Fernando Sanz-Gracia of the University of Zaragoza and the GeoDa Center for Geospatial Analysis and Computation staff at Arizona State University, in particular to: Luc Anselin, Sergio Rey and David Folch. While their help was substantial, any remaining errors are responsibility of the author. This research was supported and funded by the Spanish Ministry of Education and Science SEJ2006-04893 and AP20063563.

1 Introduction

For many decades, researchers with very diverse backgrounds, from economists to regional scientists, geographers or urban planners, have studied urban form and tried to understand what drives its spatial structure; with different perspectives and focusing on several scales, the city is the unit of analysis for many disciplines, and this interest is increasing as the world becomes more and more urban.

One topic that has kept economists particularly busy is the identification and study of employment centers. As the principal places where most part of the economic activity occurs, they have been seen as the main pillars to build upon in order to understand how cities are spatially organised. Furthermore, as today cities grow and become more complex, new structures that depart from the traditional monocentric model emerge, which makes the search and analysis of these formations a more fascinating, but also more complicated, challenge.

Although there seems to be consensus in the literature about the importance of subcenters, there is no common agreement on how they are properly measured and identified. This study aims at contributing to the last by proposing an algorithm that does not require previous knowledge of the cities of study and can thus be applied to large data sets to look for general patterns. This procedure uses at its core local indicators of spatial autocorrelation (LISA), a technique that has been applied in other fields to indentify hot-spots and pockets of heterogeneity. Departing from the LISA results, we establish a set of rules to select and pick that allow for identification, as separate phenomena, of main centers of density employment and subcenters.

The procedure suggested is then applied to the case of the US metropolitan areas, a data set of 359 cities and more than 52.000 lower-scale areas, to evaluate to which extent north american cities are polycentric. The study finds that, despite the common belief that most cities nowadays are not monocentric any more, only one main center and no subcenters were found in more than 75% of the sample.

The rest of the paper is organized as follows: section 2 contextualizes the study and overviews the principal suggestions from the literature to identify centers and subcenters; section 3 reviews LISA statistics and explains in detail the algorithm proposed; section 4 presents the database of the US metropolitan areas and applies the procedure suggested in the previous section; and section 5 concludes and points to future venues of research in this direction.

2 Different methods for one same purpose

Before overviewing the main references and suggestions made in the literature, it is important to make a distinction between centers and subcenters since, as their name indicate, they are not the same thing.

Typically, the first ones (also called central business districs or CBD's) are associated with the main employment core in the city, usually at the place where it was born and where the main economic activities have historically taken place since its beginning. Over time, economies of agglomeration[1] have created self-reinforcing mechanisms that have made those places the most productive in the city, ensuring new firms located there. This is the view reflected in the so called *monocentric city model* (Alonso (1964), Muth (1969), Mills (1972)), which has been extensively used over decades to study urban structure with proved success. However, the evolution and growth of some cities has made those initial cores less attractive due to congestion costs (including, among others, high land prices), which has led some firms to decentralize and move out of the center. If economies of agglomeration still matter for those activities, they will tend to relocate in smaller more focalized centers that provide the benefits of the CBD at lower congestion costs. These new formations have been called *subcenters* and form polycentric cities; micro-economic explanations may be found in models like Fujita and Ogawa (1982), in which this foci of employment arise because of high commuting costs and growing population.

Although there is not a unique definition of subcenter, there seems to be a common agreement on the general characteristics; as stated in McMillen and Smith (2003b), a subcenter is defined as *an area with significantly higher employment densities than surrounding areas*. Also, it *should be large enough to have a significant effect on the overall spatial structure of the urban area, leading to local rises in population dendity, land prices, and perhaps housing prices*. Last, Giuliano and Small (1991) point out the the areas conforming the subcenter need to be contiguous. However, all the agreement there is to define a subcenter is lacking when it comes to which measure or methodology use to identify them in the real world. There have been many ideas, all of them with their own strenghts and weaknesses. A brief summarizing review, not intended to be comprehensive, highlights the following four methods.

The most intuitive and one of the most popular ones is that described in Giuliano and Small (1991). They look at the case of Los Angeles and use the following definition: *a continuous set of zones, each with density above some cutoff $\bar{D}$, that together have at least $\bar{E}$ total employment and for which all the immediately adjacent zones outside the subcenter have density below $\bar{D}$*; the peak of the center is then defined as the area within the cluster with highest density. Once the cutoff is chosen, it is straighforward to recognize which areas are a subcenter and which ones are not. The problem however comes at the previous stage: defining a density level is a very subjective task and, as they show in the article, the final results (how many centers are identified) are very dependent on the treshold employed. Another important drawback of this method is that it is likely that what is an appropriate cutoff for a city,it is not for a another one, which makes hard to compare results for different cases of study.

Craig and Ng (2001) use spline quantiles to estimate density functions of distance to the CBD and identify subcenters as rising density areas. Although

[1] For a comprehensive explanation about economies of agglomeration, the reader is referred to Fujita et al. (1999).

it does not require a cutoff, the method is valid only when the CBD is known ex-ante, which implies some local knowledge to use the methodology. Also, as McMillen (2001) notes, the procedure is really identifying *rings* of high density rather than actual subcenters, and it is best suited for monocentric cities.

In a set of papers (McMillen (2001), McMillen and Smith (2003a), McMillen (2004)), McMillen defines and employs a two-stage methodology based on locally weighted regression in which, in the first stage, a density surface is created to be used in the second stage as a benchmark to analyze the sign of the residuals and pick as subcenter those statistically positive. This method has the advantage that it does not require as much subjetivity as in the cutoff one, since the decision of which areas are a subcenter and which ones are not is left to the statistical significance of the residuals. However, as Griffith and Wong (2007) point out, it requires the assumption that employment density follows some general pattern from which subcenters positively deviate.

A more recent strand of the literature is the one using exploratory spatial data analysis (ESDA) and local measures of spatial autocorrelation as a tool to identify the subcenters; some examples include Baumont et al. (2004), Riguelle et al. (2007) and Griffith and Wong (2007). This technique has been used before in other fields to find clusters or hot-spots and, when applied in this context, has proved able to identify centers and subcenters successfully; furthermore, it may be used in ways that do not require local knowledge of the urban area or any previous assumption about its distribution of employment. Since the methodology proposed here uses them as the core of the procedure, we provide a deeper explanation of what they are and how they work in the following section.

3 Identification of centers and subcenters using ESDA

As we have seen above, many alternatives have been suggested to indentify employment centers and subcenters in urban areas. The present work uses local indicators of spatial association (LISA) as the core of the algorithm proposed. But, before we get into the details, let us explain what LISA are and what they are dessigned for.

3.1 Local Indicators of Spatial Association

The family of LISA statistics are part of a set of techniques called exploratory spatial data analysis (ESDA), whose main purpose is the exploration of phenomena in which space is particularly relevant and the detection of spatial patterns that may not be noticed by using traditional techniques. There are basically two main branches of ESDA tools: global and local. The first ones give an overall sense of the presence of spatial autocorrelation while the second ones are employed to detect study of heterogeneity and local deviations from the general behaviour that may be hidden if the analyst uses only global measures. Obvious uses of the last ones include the analysis of spatial clusters and hot-spots as well as detection of outliers. In this case, due to the particular nature of the topic of study, we will only employ the local version, as our purpose is to detect foci of significantly high values.

There are several variants of local indicators to analyze spatial autocorrelation. The LISA (Anselin (1995)), as defined in the original work, are local spatial statistics that indicate *significant spatial autocorrelation* for each location. One of the nice properties of this kind of indicators is they may be summed up into their corresponding global indicator. Our choice here is the local version of the Moran's I, whose expression is:

$$I_i = (\frac{z_i}{m_2}) \sum_j w_{ij} z_j, \tag{1}$$

where z_i is the standardized variable of interest, m_2 is its second moment (variance) and w_{ij} is the spatial weight given to the observations i and j. Positive values of I_i indicate presence of positive spatial autocorrelation (of either high or low values) and are used to identify clusters, while negative values indicate negative autocorrelation (either high-low of low-high) and usually point to outlier observations. In order to perform inference, we take the conditional permutation approach, in which the observation i is held fixed and the neighboring values are permutated several times following a spatially random process. The statistic is computed for each of such permutations and, based on those values, the empirical distribution is constructed, allowing to obtain *pseudo* p-values of significance.

One of the main drawbacks of the local version of Moran's I is that it distinguishes between positive and negative spatial autocorrelation but, provided an observation displays a positive value, it is not possible to discern whether it is a case of a high value surrounded by high values (HH from now on) or a low value with low values as neighbors (LL from now on). In our particular case, this is crucial in order to identify specially dense (and not specially not dense) areas of employment. For this purpose, we use another ESDA tool, called the *scatter plot*. This device represents the variable of analysis on the horizontal axis and its spatial lag (an average of the neighboring values of each observation) on the vertical axis. This way, it may be observed what kind of relationship every observation has with its neighbors and thus allow to make a distinction between HH (first quadrant) and LL (third quadrant) values.

3.2 *When is it a center and when a subcenter?*

In this section, we explain the rationale behind the algorithm proposed to identify centers and subcenters of employment density in urban areas and detail each step of the process. As we have noted above, main centers and subcenters are different phenomena caused by different reasons and, as such, they should be treated differently when trying to identify them. Keeping that in mind, we suggest a procedure that operates in two stages: in the first one it identifies the main center(s) of the city, using a restrictive rule so only those areas with extraordinary high employment density get picked; in a second stage, areas with less high (yet statistically significant) density are labelled as subcenters by applying a more *liberal* rule.

3.2.1 Pre-requisites

This method is meant to identify centers and subcenters in urban areas; although in an ideal world, density is a continuum phenomenon, in reality it is only possible to measure urban employment density in a discrete fashion. For that purpose, we need an intra-urban scale unit that aggregates to the total urban area, it has certain degree of refinement and for which employment density may be computed. In the remaining, this sub-unit will be called *area*.

In order to carry out statistics of spatial autocorrelation and to find the centers and subcenters of the city, we will need a conceptual representation of the actual geography of the region. The way this is usually done is by means of a spatial weights matrix (W) of n by n elements in which the elements of the diagonal (w_{ii}) are zero and the rest (w_{ij}) receive a weight expressing the spatial connection between the two elements (i and j). There exist many kinds of rules to determine w_{ij}, being the most common spatial contiguity and distance based. Although here we employ spatial contiguity, any matrix that reflects neighboring relationships between the areas should be fine.

Once we have density values per area and a spatial weights matrix, the first step to follow is to compute local Moran's I for each area and obtain their standardized (z) values; then, following the permutational approach as stated above, we will construct the empirical distribution and compute the *pseudo* p-values, which will later be the base of the selection of the centers and subcenters. The last pre-step before getting into the algorithm is to obtain the scatterplot of the employment density and to keep the quadrant in which each area is located in order to be able to discern between HH and LL situations.

3.2.2 Restrictive stage: the main center(s)

This stage is meant to identify the main center(s) or CBD('s). Since these clusters are by definition larger and the principal focus of activity, we need a *conservative rule* to make sure the ones picked as such are in fact the most important ones in the area. We impose two conditions for an area to become a candidate center:

1. It needs to be a value located in the first quadrant of the scatterplot (HH).
2. It is required to be statistically significant at a *low* significance level. Although it is decision of the researcher to pick a particular level, we suggest to use at least 0.1%.

If an area meets the above two conditions, we will label it as a *candidate* and will consider it and all its neighbors as a potential center. The justification behind this choice is that the candidate represents the core of a concentration of high values, but the whole cluster is compounded by the core and its neighbors.

The previous conditions ensure the candidates are relevant enough foci as to be considered a center. However, because the LISA recognizes only the core, it might be the case that, when adding the neighbors to conform the full cluster, two candidate centers happen to be contiguous. In this case, we interpret they are both part of same center and thus join them in only one cluster, keeping the core with lowest *pseudo* p-value as new core. Once this contiguity check has been performed, the resulting clusters will be considered as main centers of employment.

One last note regarding the first stage needs to be commented: it may be the case that none of the areas result statistically significant at the level chosen. This could be due, among other reasons because employment is too evenly dispersed across the urban region (i.e. there is very little heterogeneity) and thus no hot-spots appear. In this case, we will consider the area with the minimum *pseudo* p-value as the only candidate and label it and its neighbors as the main center.

3.2.3 Permissive stage: subcenters

The second stage of the algorithm is intended to pick subcenters, which are areas of relatively high employment density, not enough to make it into the category of main center, but still showing significantly high values; furthermore, these are areas typically (although not neccesarily) smaller than the main CBD. Because of those two characteristics, we adopt a slightly different approach than in the previous stage. The initial conditions for an area to become a candidate only differ in the degree of permissiveness, which is risen. In this case, an area needs to:

1. not to be part of any of the main centers.
2. not to be contiguous with any of the main centers.
3. be a high value surrounded by high values (HH).
4. be statistically significant at a *more liberal* level of significance. Again, the final choice needs to be made by the analyst, but in this case we suggest to use levels around 5%.

The first condition is obvious, and the second one is set to avoid picking as a subcenter areas that may still be in the area of incluence of the main center but do not have levels high enough so as to be part of them. In the third one we rise the level of significance so more areas may show statistical significance and be elected as potential subcenter candidates.

Once an area is selected as a subcenter candidate, we do not add its neighbors as part of the cluster. The rational behind this decission is that subcenters are very focalized areas of higher employment; moreover, the fact the significance level has been lowered implies that the reliability with which the areas are selected decreases and thus the probability the surrounding areas are also part of the actual subcenters is lower.

Regarding the rule applied to join candidate areas, in this case, since subcenters are more focalized formations, we adopt a less *extensive* approach and only join those candidates that share, at least, one neighbor[2]. This is done because if a non-candidate is directly surrounded at the same time by, at least, two candidates, we think it is likely to be part of a center formed by itself and the candidates.

4 Looking at the polycentricity of the US cities

In this section we apply the algorithm explained above to analyze the case of the US urban areas and determine to which extend they can be named polycentric as they have usually been called, or monocentrism still holds as a general rule. We first introduce the data set employed, then outline the details of the study and finally present the main results and conclussions.

4.1 Data set

As stated in the previous section, in order to be able to employ the method proposed, two kinds of units of analysis at two different scales are needed: the first one refers to the aggregated city or urban region, and the second one needs to be a disaggregation of the first one into finer resolutions.

The city here is represented by the Metropolitan statistical area from the US Census Bureau, in its version of june 2003. This definition is sufficiently broad as to capture the concept of urban region and all the internal interactions inherent to a city, as well as it provides an excellent data availability. The choice for the intra-urban unit is the census tract, also from the US census bureau; it provides a good mix between data availability and refinement of scale. Table 1 gives a sense about the dimensions of the data set employed.

The data for employment were deduced from database of commuting data for the year 2000 from the US Census Bureau. In its raw form, this database indicates the tract of origin (place of residence), tract of destination (place of work) and the number of people that commute between the two of them. These data were processed to extract only the commutes taking place within the same MSA and the commuters were added by place of destination (work) to obtain data of employment at the tract level.

Last, geographical data were obtained from the database TigerLine also by the US Census Bureau, and the areas were calculated using the open-source

[2] In this case the shared area needs not to be neighbor of any of the main centers for the join to be effective

	N	Min	Max	Mean
MSA	359	18.323.002 New York-Newark-Edison (NY-NJ-PA)	16180 Carson City (NV)	640.335
Tract	52328	0	36146	4.393

Note: the min, max and average are based on population data.

Table 1: Summary statistics of the data set

library pySAL (Rey and Anselin (2007)). The density of employment for each tract was then computed by applying the spatial Empirical Bayes smoothing, in order to minimize the problem of variance instability instrinsic of rates. If not dealt with, this issue may lead to spurious inference for Moran's I (Anselin (2005)).

4.2 Employment centers and subcenters in US cities

The methodology proposed was applied for the US metropolitan areas. Previously, local Moran's I had been computed for every MSA and the estimates needed according to section 3 were kept to be passed to the algorithm. We employed binary weights matrices of simple contiguity following the *queen* criteria and the tresholds used to identify the centers and subcenters were 0.01% and 5%, respectively. One more technical note that needs to be added is that we did not allow areas with more than 10 neighbors to become part of a cluster (neither for the main centers nor for the subcenters). The reason of this exclusion is that we realized, in urban areas, populated tracts tend to have a much lower average of neighbors and it is only *empty* tracts (parks, reservations, etc.) that display such a high number of neighboring areas. Letting them be part of clusters resulted in artificially joined clusters where these areas were acting as *bridges* connecting separated centers/subcenters.

Figures 1 (a) to (d) show four examples of the output of the algorithm. The main centers (CBD's) are displayed in yellow, their cores in red and green areas correspond to the identified subcenters. In the case of Los Angeles, one of the cities that have been labelled as polycentric most often, the algorithm found 12 foci (3 main centers and 9 subcenters), scoring as the most polycentric city of the sample[3]. New York, however, being larger than LA, only showed one main center located in the middle and lower Manhattan and in the western part of Brooklyn and six subcenters located mostly in the upper Manhattan. Phoenix

[3] Only four cities among the 359 msa's were found to have more than one main center/CBD: Los Angeles, archetype of polycentric city; Riverside, which is the msa right south of LA and could be considered as the extension of the same structure of LA; Milwakee, in which further inspection revealed that the two centers were artificially created by the existence of a river that breaks the normal contguity relationships; and Oklahoma, that appears to be an outlier as it displays two sepparated CBD's

is considered as good example of low density and *sprawl* and the algorithm found one main center and 6 different subcenters, the third highest number (just behind LA and Riverside). On the contrary, Portland is usually considered as a compact city (partly due to the existence of growth boundaries) and, as such, only displayed one CBD and no subcenters, typical picture of the traditional monocentric city.

Min	**Max**	**Mean**	**Monocentric**
1	12	1.49	279 (78%)

Table 2: Summary of the results of the algorithm

Table 2 shows a summary of the number of centers found for all the msa's. The first striking result is the fact that, according to this method, more than three quarters of the cities only have one main center and no subcenters (like the Portland example).

This broad picture of a monocentric majority is reaffirmed in figure **??**, which show the kernel estimation of the density distribution of the number of centers. As it is clear, the highest peak is around 1 and the curve rapidly plunges in almost the same way to the left as to the right.

The main conclussion that may be extracted from these results is that, despite the belief that cities are not monocentric any more, many of them still base most of their economic activities in one agglomerated area and if we interpret these results in terms of the polycentric city economic models, it appears that most of the US cities still have not reached the population/commuting-cost breaking point required for a subcenter to emerge.

5 Conclusions and future directions

This study started highlighting the relevance of the analysis of centers and subcenters of employment density in urban areas. Despite its importance and the fact that several methods have been suggested, there does not exist common agreement on how to measure these phenomena in the real world. An algorithm fundamentally based on local indicators of spatial association (LISA) is proposed to identify centers and subcenters in two sequential stages that does not require local knowledge and that may be applied to large data sets to look for patterns and general behaviours. The procedure is then applied to the US metropolitan areas in order to evaluate the degree of monocentrism/polycentrism that exists.

One of the final conclussions of this article is that most of the US cities in 2000 still showed high evidence of being structured around only one center. The same result may be viewed inversely and think that, at the beginning of the new century, almost a quarter of the cities in the US had departed already from the traditional structure of only one center. An interesting question left for future research is weather this apparent rate of one polycentric city per 3 monocentric has stayed constant over time or it reflects just a transitional state towards a future polycentric world. Looking at the previous composition of the distribution that gave the snapshot analyzed here for 2000 seems then to be a fascinating way to try to depict tomorrow's urban structures.

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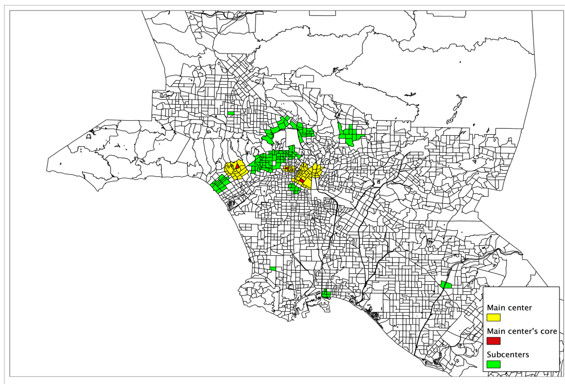
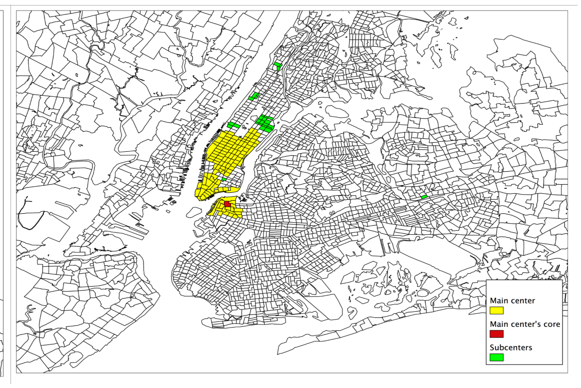
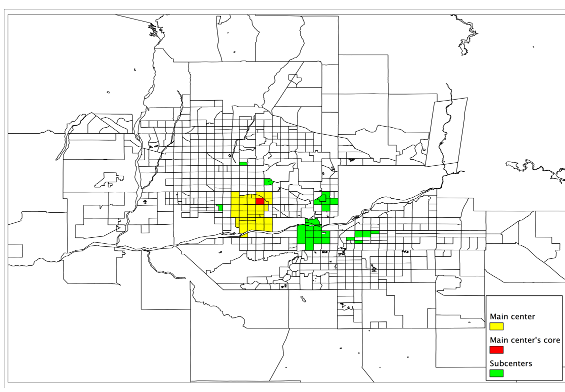


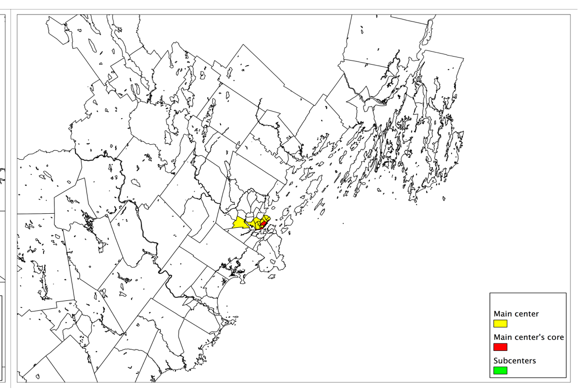
(a) Los Angeles



(b) New York



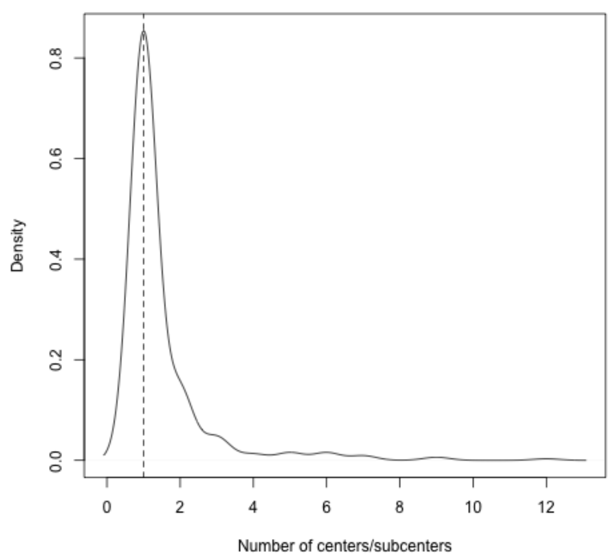
(c) Phoenix



(d) Portland

Figure 1: Examples

Note: for the ease of visualization, the maps represent the area of interest (where the centers and subcenters were identified) zoomed, not the whole MSA region.



Dashed line corresponds to 1

Figure 2: Kernel density of the distribution of centers