

68 Mission Park Drive Williamstown, MA 01267 413-597-4461 www.c-3-d.org

# Culture Concentrations

Stephen Sheppard <sup>1</sup>

November 2, 2014

<sup>1</sup>Department of Economics, Williams College, 24 Hopkins Hall Drive, Williamstown, MA 01267.

The research reported in this paper was made possible through the support of the National Endowment for the Arts, ArtWorks award 12-3800-7003. The views expressed in this report represent those of the author and are not necessarily endorsed by the National Endowment for the Arts or the staff thereof. This research has had the benefit of assistance from Kay Oehler, Williams College Center for Creative Community Development. Her efforts have improved and helped to extend the research. Helpful comments and feedback on a previous draft were provided by Paul Cheshire, Kurt Schmidheiny and participants in the Vrije Universiteit Amsterdam Workshop on Cultural Heritage and Urban Revival. Errors and omissions are the responsibility of the author.

#### Abstract

Many cities contain local agglomerations of cultural organizations. The "Museum Mile" portion of 5th Avenue in New York, the Museumplein in Amsterdam, Exhibition Road in South Kensington, London are famous examples, and there are hundreds of others large and small. These clusters may arise for some of the same reasons that other agglomerations occur, although the cultural organizations that comprise them have more complex objective functions than the profit-maximizing firms whose agglomeration is more frequently studied. In this paper we assemble micro-geographic data on cultural non-profits in US urban areas from 1989 through 2009. We calculate several indices of concentration and dispersion, and assemble a panel data set to explore the impact of these concentrations on local economic well-being. We also present evidence consistent with a hypothesis that there are real agglomeration economies at work, lowering production costs and permitting a larger number of cultural organizations *per capita* in urban areas where the organizations are more clustered.

# 1 Introduction

The past two decades have seen increasing interest in spatial concentrations of both the production of and enjoyment of the arts. Interest in cultural districts, culture clusters, cultural neighbourhoods and cultural cities has come from those with academic, public policy, commercial and aesthetic interests in the arts.<sup>1</sup>

In the United States, there are at present more than 180 designated cultural districts under enabling statutes that exist in 8 states. Of these 132 are located in one of 48 different metropolitan areas.<sup>2</sup> These designated cultural districts provide a variety of benefits, ranging from simple recognition of the neighbourhood or community to exemption from sales and income taxes for artists and commercial galleries that are located within the designated areas.

Whatever the benefits to artists and arts organizations provided, one central idea lies at the foundation of all of these designations: concentrations of culture providers, culture producers or organizations that facilitate the arts is a good or at least noteworthy thing. Whether this is actually true seems, at the very least, to be an empirical question whose answer may depend on circumstances and the goals one has in mind. If the goal is to maximize the well being and success of the individual cultural organizations who are clustering, it might be that grouping them together increases the competition and rivalry that exists between them, leading them to cut admission prices or stage more elaborate productions in pursuit of a mission that dictates serving the largest possible audience.

Alternatively, it might be that they are subject to agglomeration economies. These improvements in efficiency come about when organizations, particularly those engaged in similar activities, are located close to one another. These economies have been observed by economists in one form or another since Adam Smith and have been elegantly summarized by Rosenthal & Strange (2001). If these economies are operative, then being clustered together might permit cultural organizations to share inputs or learn and be inspired by each other, making them more efficient. These efficiencies and the lower costs of production that result may enable them to produce higher quality experiences for their audiences and patrons, and for more of them to be operative in a given urban area.

Potential tensions suggesting that culture clusters might be either desirable or undesirable may also arise if the goal is to maximize the economic benefit or the level of prosperity achieved in the city. Locating cultural destinations close together may enhance the value of the city as a cultural destination. It is easier for visitors or cultural tourists to learn about what is available and access it from a single location if culture is concentrated.

<sup>&</sup>lt;sup>1</sup>See, for example, Lorenzen & Frederiksen (2008) and Stern & Seifert (2010).

<sup>&</sup>lt;sup>2</sup>See the report by the National Association of State Arts Agencies NASAA (2012).

Alternatively, we might argue that the source of economic benefit of cultural organizations is that they inspire and educate, creating a more creative workforce for the city. If this is true, it seems likely that spreading the organizations throughout the urban area may enhance the economic impact because it improves access of residents to cultural organizations that are no longer in some remote city center location but are now in the local neighbourhood.

How can we measure and compare culture concentrations, and which factors affect the concentration of cultural organizations in a group of urban areas as diverse as the US urban system? Traditionally, the presence of cultural clusters would either be established by a variation of the case study method, in which the analyst becomes familiar with the organizations in a city, observes the patterns of audience patronage and perhaps collaborations between organizations, and then declares, maps, and analyzes the impact of these clusters. There are several examples of this approach. For example the study of cultural districts in Philadelphia presented in Stern & Seifert (2009) identifies cultural districts and relates their presence to changes in house prices and other measures of the local economy. Markusen & Johnson (2006) study local art centers in several small cities and towns, documenting their evolution and impact on local neighbourhoods. This approach is attractive for its ability to present a nuanced perspective of both the local cultural organizations and the local economy. The limitation of this approach is that it is impractical for application to a large number of cities, an application that is essential if we are to undertake careful statistical testing of the impact of clusters of cultural organizations on local and regional economic development.

Alternatively, data can be collected on the number of museums, performance venues and other cultural organizations and the analyst can calculate the number of organizations within a specific spatial area or unit. For example we might map the total number of cultural organizations in each zip code or county, and compare them. Because both zip codes and counties (and census tracts and states and almost all areal units for which data might be aggregated) vary in size, we might try to standardize the measurements by presenting the numbers of organizations *per capita* or *per square kilometer*. The difficulty with this approach is that it is subject to what is known as the *Modifiable Areal Unit Problem* sometimes simply referred to as *MAUP*. This problem occurs because the size of spatial units varies across observations, and even adjusting by presenting the data on a *per capita* or *per square kilometer* basis does not correct for the fact that any analysis of the data is both an analysis of the aggregation scheme (presenting the data at the county or zip code level, for example). Such analysis also has difficulty identifying clusters or spatial structure and a wide variety of scales. We might see no clusters at the individual census tract level, but miss the fact that the entire county is a concentration of such organizations. Similarly, we might declare a metropolitan area to be lacking in cultural

organizations based on the number of such organizations *per capita* or per unit area, but miss the small scale structure of cultural organizations in one particular neighbourhood. Despite the difficulties, many examples of this type of analysis exist. A widely-read example is the analysis presented in Florida (2002) but virtually any study that compares cities based on the number of organizations or sources of cultural production within the city, county, or other arbitrarily drawn area is vulnerable to this criticism.

In this paper we present an alternative that addresses some of the challenges to these two methodologies. We want an approach that can be applied at moderate cost to a large number of cities for comparison and analysis, but is capable of detecting clusters at different scales and is less dependent on the spatial units into which data are aggregated. To understand this approach, we identify a group of measures that can be applied to a large number of cities and that avoids the *MAUP*. These measures provides us with a group of potential indicators of concentration for cultural organizations. Using these we can explore, using a panel of 21 years of data from US metropolitan areas, the impacts of concentration on cultural organizations and the impacts of culture concentrations on the local economy.

Using these data, we provide an investigation of the impacts on concentration of culture producers in a way that provides a test of the strength of agglomeration economies for cultural organizations. We also investigate the impact of culture concentrations on the level of well-being in the local economy.

Despite the centrality of these questions in addressing the nature and importance of the cultural sector and public policies that support it, there have been few studies that examine the impact of the spatial structure of cultural organization location on economic outcomes. Policy makers seeking to allocate the scarce funds available for supporting these organizations can potentially make better decisions if these relationships are better understood. The goal of this paper is to make a contribution toward such understanding.

## 2 Measuring culture concentration

When we examine the patterns of locations occupied by cultural organizations, it can be difficult to know whether the pattern has arisen due to natural or economic forces that enhance the sustainability of culture producers that are concentrated at particular points, or the product of accident arising from random location choices. Whether it is better to call the clusters that do occur *natural* or *accidental* depends on what is expected to occur. Such expectations are generally based on experience in actual cities and from looking at the location patterns of other similar organizations.

In this section we develop measures of how the concentration of cultural nonprofits compares to the con-

centration of other nonprofit organizations. This is inspired by the analysis of industrial location first presented by Duranton & Overman (2005) and applied by them to analyse the location of manufacturing in Britain in Duranton & Overman (2008). The approach has since been applied to describe and analyse location, co-location and the effects of policies in a variety of settings<sup>3</sup>.

The essential idea is to compare the distribution of distances between organizations with the distribution of distances between some reference set of locations. We compare the distribution of distances between cultural nonprofits with the distribution of distances between all other nonprofit organizations within each metropolitan area. Rather than consider only similar organizations within a set distance as done by Duranton & Overman (2005) we consider all organizations within the MSA boundaries<sup>4</sup>.

The distribution of distances between organizations in a given area depends on the number of such organizations. In order to construct a valid comparison, we follow a procedure similar to Duranton & Overman (2005), drawing repeated random samples of size equal to the number of cultural nonprofits in the city. A *kernel density* estimate of the distribution of distances between organizations is calculated for the cultural nonprofits as well as for each of the sample draws from the population of all nonprofits in the urban area. This process determines a range of possible densities for each distance between nonprofit organizations.

The median distance between all cultural nonprofits in the urban area provides an overall measure of concentration and when necessary will be represented by the  $\theta$ . If the density of cultural nonprofits rises above the 95<sup>th</sup> percentile of the density distributions of all nonprofits at a distance less than half of the maximum distance between nonprofits in the city, we say that the cultural nonprofits are *clustered* and set the indicator variable  $\lambda = 1$ . In addition, we provide counts of the number of distinct distances where the density for cultural nonprofits rises above the 95<sup>th</sup> percentile of distributions for all nonprofits. This count  $\rho$  of *significant peaks* provides some information about the number of distinct cultural clusters in the urban area. The count  $\rho$  is not a count of distinct cultural clusters, but as the number of distinct concentrations in an urban area rises, the value of  $\rho$  will tend to increase. The distance where the density of cultural nonprofits exceeds or comes nearest to the 95<sup>th</sup> percentile density of all nonprofits is calculated to provide a measure, represented by  $\theta_{\delta}$ , of the scale of the most common or most important cultural clusters. The numerical magnitude of the gap at this distance, between the 95<sup>th</sup> percentile density for all nonprofits and the density of cultural nonprofits, is represented by  $\delta$ and provides a measure of the dominance or importance of clusters at this scale.

Figure 1 provides three examples that illustrate the measures. In each of the maps, the locations of other

<sup>&</sup>lt;sup>3</sup>See for example Billings & Johnson (2014).

<sup>&</sup>lt;sup>4</sup>As of 2009, determined by the Office of Management and Budget in OMB (2009)

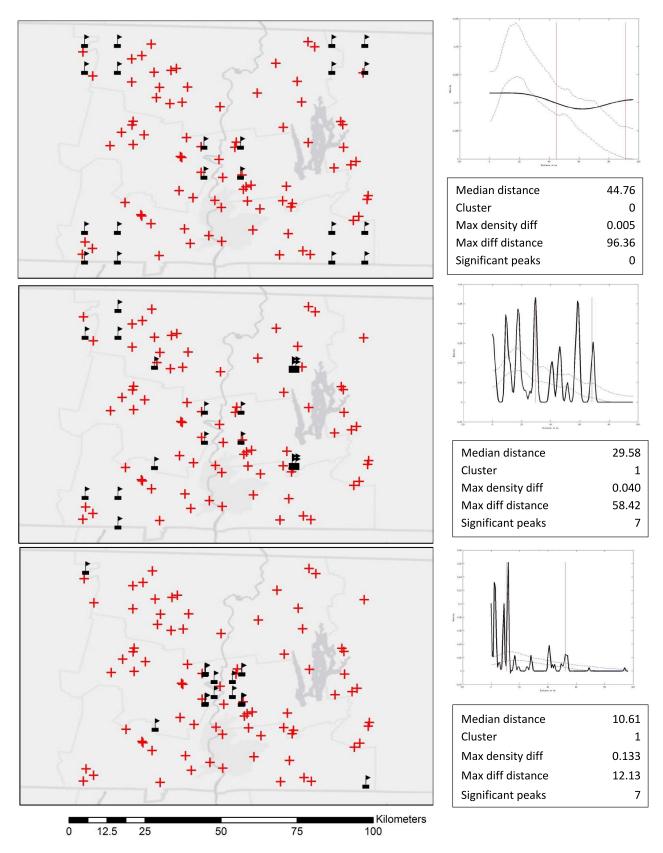


Figure 1: Three illustrations of comparative cluster measurement

nonprofits are indicated by the + symbols, and the illustrative locations of cultural nonprofits are represented by the **L** symbols. In each of the three cases, there are 20 cultural nonprofits, and 80 other nonprofits. The locations of the other nonprofits were chosen randomly. In each example the locations of the cultural nonprofits were chosen to illustrate different types of concentration and clustering. Locations in the figures are displayed over a representative geography.

In the first example at the top of the figure, the cultural nonprofits are scattered throughout the region. They do have a very loose structure, being located in dispersed groups of four organizations, at the vertices of rectangles that are about 9 kilometers wide and 10 kilometers tall. While this certainly represents some **spatial structure**, it represents less **concentration** or localized clustering than the randomly located other nonprofit organizations. To the right of the map is a graph. The darker line is the distribution of distances between the 20 cultural nonprofits, and the two lighter grey lines show the upper 95<sup>th</sup> and lower 5<sup>th</sup> percentiles of the distribution of distances between other nonprofits. The two vertical lines show the median and 95<sup>th</sup> percentile separation distance between simulated cultural nonprofits.

The distribution of cultural nonprofits does not rise above the  $95^{th}$  percentile in the range of separation distances less than 50 kilometers, and in fact is below the  $5^{th}$  percentile so actually exhibits dispersion relative to all nonprofits. The median distance of 44.76 kilometers is relatively large.

In the second example we see clear signs of concentration. Here the two groups on the east side of the map are clustered together more closely. In each of these groups the four organizations are within 1 kilometer of each other, and the two clusters themselves are closer to each other and to the other organizations in the region. The impact on the cluster measures is clear. The median distance has dropped to 29.58 kilometers, and there are several places where distribution of the cultural nonprofits rises above the 95<sup>th</sup> percentile of the distribution of other nonprofits at relatively small separation distances. The nonprofits in this diagram are clustered. The procedure identifies seven significant peaks, three or four of which are in the first half of the range of observed distances separating organizations. This matches reasonably well with observation of the map, where the two clusters on the near east side plus the looser 'cluster' consisting of those two clusters along with the four organizations near the center of the map.

The distances at which local significant peaks occur can be difficult to interpret. Some intuition may be had by considering the following interpretation. Suppose there were an equal number of cultural and other nonprofits. Suppose that we analyse the distribution of nonprofits in an urban area and note a significant peak in the distribution at some separation distance  $\delta$ . What this means is that if we took a card and cut a circle of diameter  $\delta$  in it and passed it slowly over all the areas of the map, the *share* of cultural nonprofits that would, in some locations, be visible through this circle would be much larger than the share of other nonprofits. This thought experiment also helps to develop an understanding of why this approach is so powerful. It is capable of identifying spatial structure or clustering at many different scales. There might be some 'walkable' clusters on the scale of organizations located within a few hundred meters of each other. There may be 'neighbourhood' clusters that are a few kilometers across, and there may be 'regional' clusters that are tens of kilometers in diameter.

Finally, the third example presents a very concentrated example. There are four individual organizations near the center, each separated by 4 to 5 kilometers. Just outside these are four more dense clusters, each with several organizations located within 150-300 meters of each other. These clusters are so dense that we cannot really tell how many symbols are printed in each location. This presents a scale of clustering consistent with patrons or employees being able to walk between organizations and matches the kind of density observed in some well-known cultural clusters. The structure is clearly revealed in the analytics, as well. The distribution easily satisfies the definition of being clustered, and has a median distance of 10.6 kilometers. The number of clusters we could visually identify in the map probably exceeds the number of significant peaks at relatively small scales of separation, but the maximum density difference observed - particularly at separations of approximately 3 and 12 kilometers - suggests that those peaks are actually counting multiple clusters of cultural organizations.

In order to further develop an intuitive feeling for these measures, it can be helpful to make some comparisons between actual cities with which we might be familiar. Towards that end, consider Figure 2, which presents a comparison of the estimated 2009 distributions for Los Angeles and New York City. The dark solid lines present the estimated density of cultural non-profits by distance of separation. The two metropolitan areas are of similar widths, and the graphs have been scaled so that the horizontal dimensions, ranging from 0 to 120 kilometers, are aligned and can be compared. The vertical dimensions are not equal because New York's distribution is much more concentrated so the density at small distances of separation are much greater.

In each graph, there are two vertical lines. The one on the left represents the median distance of separation.<sup>5</sup> New York's is much smaller - 4.39 kilometers - than in Los Angeles where a pair of randomly chosen cultural nonprofits has even odds of being almost 20 kilometers or more apart. The dashed lines present two bases for comparison. The blue lines represent the  $95^{th}$  and  $5^{th}$  percentiles of the density distributions of all nonprofits in the urban area. The green dashed lines represent the  $95^{th}$  and  $5^{th}$  percentiles of the density distributions of all zip+4 locations in the urban area, presented to approximate the distribution of the built environment of the city.

<sup>&</sup>lt;sup>5</sup>The vertical line on the right represents the 95<sup>th</sup> percentile of separation distances between cultural nonprofits.

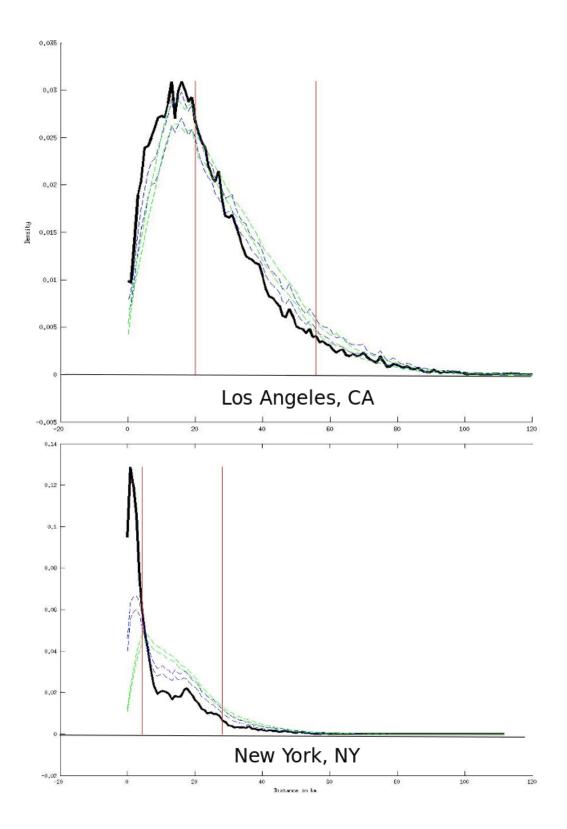


Figure 2: Comparative analysis of Los Angeles and New York City in 2009

Both cities exhibit clustering. New York does so very clearly, but so does Los Angeles. New York exhibits only one significant peak, but it is extremely high relative to all nonprofits, representing the concentration of cultural organizations in Manhattan. Los Angeles, by contrast, has cultural organizations that are more concentrated than nonprofits as a group, but not by much. It has several significant peaks - five - indicating separation distances at which the density of cultural nonprofits is greater than that of all nonprofits.

Overall, it must be observed that this comparison fits with the common understanding of these two large cities. New York cultural organizations are highly concentrated in Manhattan, making this center of the city exciting and vibrant. It does have the consequence of making the outer boroughs and nearby areas of White Plains and northern New Jersey feel less accessible to cultural organizations. The cultural assets of Los Angeles, by contrast, feel more 'spread out' and this is revealed in the data.

In summary, we have applied a variation of the microgeographic analysis of location introduced by Duranton & Overman (2005) and from that analysis derived several measures that can be used for analysis of culture concentrations. With a series of examples, we have shown the potential value of five different measures of clustering or agglomeration of cultural nonprofits:

- 1. A dichotomous cluster indicator variable  $\lambda$  that indicates whether at some scale cultural nonprofits are more clustered ( $\lambda = 1$ ) than all other nonprofits;
- 2. The median distance  $\theta$  between cultural nonprofits;
- 3. The number of significant peaks  $\rho$  distinct distances at which the density of cultural nonprofits exceeds the  $95^{th}$  percentile of the density on all nonprofits;
- 4. The maximum difference  $\delta$  between the density of cultural nonprofits and the  $95^{th}$  percentile of the density on all nonprofits;
- 5. The distance of separation between organizations  $\theta_{\delta}$  at which this maximum separation occurs.

All of these measures, based on microgeographic data about the location of organizations, avoid the distortions of measuring the numbers of organizations per census tract, zip code, county, metro area, or state. As mentioned above, these more traditional measures of concentration make comparison between cities or regions more difficult or impossible.

#### **3** The impact of culture concentrations

Consider an organization operating to produce cultural services in a setting where other organizations producing similar services may choose to operate. These might be organizations of any type, ranging from major art museums with internationally important collections, to performing arts centers, to small cultural centers or arts schools serving local and more specialized audiences. The key characteristic of these organizations is that they operate as *nonprofit organizations*. Such organizations want to serve a large audience, but are subject to the constraint of *economic sustainability*. This requires that they cover the costs of providing for the creation, curation, display, performance, and education concerning the artistic works that are their focus, in whatever combination bests fits the mission chosen by the governing board of the organization. This is similar to a process of competition in an economy where the producers of goods or services face demands for their products and choose to operate if they can cover all costs. If they cannot, they do not open (or do not survive).

To provide the outline of a more formal model, it is straightforward to adapt the closed economy model of Melitz & Ottaviano (2008) in a way that reflects potential agglomeration economies and provides insight concerning the expected impact of greater agglomeration on the total economic output of the region and the total number of cultural organizations active in equilibrium. We provide the outline of such an interpretation here, retaining the notation of Melitz & Ottaviano (2008) for ease in comparison.

Consider a region of L identical consumers, each having preferences that are separable between cultural goods and services and other goods. Cultural goods and services are produced by cultural organizations and indexed by indexed by  $i \in \Omega$ . Total consumption of all culture is given by

$$Q^C = \int_{i \in \Omega} q_i^C di \tag{1}$$

Households derive utility from these goods and supply one unit of labour to earn income used to purchase cultural goods. Separable utility permits focus on the allocation of this income amongst the cultural goods. Expenditures on other goods is not, and need not be, of concern in the discussion below.

Consumers have identical utility functions, and the portion of their utility function that determines the utility of cultural goods is as described in Melitz & Ottaviano (2008), so that the inverse demand for each type of culture is given by:

$$p_i = \alpha - \gamma \cdot q_i^C - \eta \cdot Q^C \tag{2}$$

for  $q_i^C > 0$ . Thus  $\gamma = 0$  implies that cultural goods are perfect substitutes and consumers care only about the

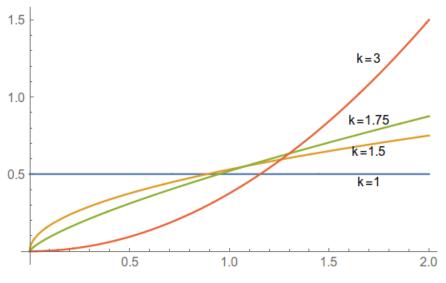


Figure 3: Distribution of marginal cost at alternative values of k

total of all such goods consumed. As  $\gamma$  increases the cultural goods become increasingly differentiated from one another.

The subset of culture consumed is  $\Omega^* \subseteq \Omega$ , identified by the set of indices for which the price of the good  $p_i$  is less than the price that would make demand  $q_i^C = 0$ . The measure of goods varieties consumed  $\Omega^*$  is N. The average price of cultural goods consumed is:

$$\bar{p} = \frac{1}{N} \cdot \int_{i \in \Omega^*} p_i di \tag{3}$$

As noted in Melitz & Ottaviano (2008) this demand system exhibits a preference of variety so that the utility of consumers rises as N increases, which seems sensible for an economy that values a variety of cultural activities.

The cost of producing culture c is a random variable whose reciprocal  $\frac{1}{c}$  (which can be thought of as the *efficiency* of the organization) is distributed according to a Pareto distribution with scale parameter  $\frac{1}{c_m}$  and shape parameter k, with  $k \ge 1$  required for efficiency to have a finite mean. The value of the parameter  $c_m$  is the maximum marginal cost of production for culture. When k = 1 the marginal cost values c are uniformly distributed between 0 and  $c_m$ . As k rises, the distribution becomes less favourable for cultural production, bunching organizations increasingly towards the higher cost portion of the interval  $(0, c_m)$ . Figure 3 illustrates the distribution for four alternative values of k, all with maximum marginal cost  $c_m = 2$ .

Each cultural organization that enters this market produces a single variety of cultural good or service, and must pay a fixed cost  $f_E$  to enter the market. After paying this fixed cost, the culture producers learn the constant marginal cost of culture production  $c \in (0, c_m)$  where  $c_m$  is the upper bound of possible marginal production costs. The level of fixed costs  $f_E$  associated with opening in the market, along with the level of demand, will determine a maximum sustainable cost level  $c_D$ , where the organization revenues are just capable of covering production costs. We follow Melitz & Ottaviano (2008) in assuming that the level of  $f_E$  and other parameters are such that  $c_D < c_m$  and the equilibrium with free entry of organizations produces a well-defined solution. Organizations whose costs c are below  $c_D$  will operate and produce the cultural goods  $i \in \Omega^*$ , and as noted above there will be N of these.

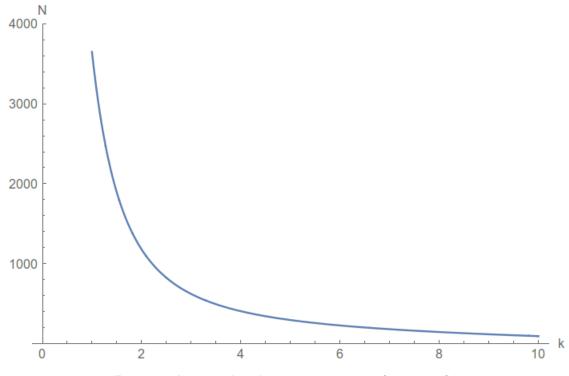


Figure 4: Active cultural organizations as a function of k

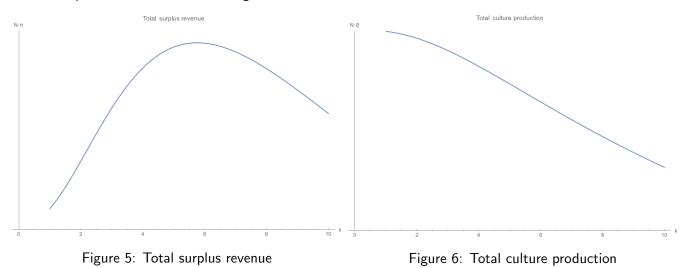
The shape parameter k for the Pareto distribution of efficiency levels is critical in determining the number of active organizations in the region, the aggregate level of surplus revenues, and the level of culture production in the region. Melitz & Ottaviano (2008) show that there is a cutoff level of costs  $c_D$  that determines which organizations will be active producers in equilibrium. If the random variable  $c > c_D$  then the organization will not be active. For the cost distribution identified above this cutoff level of costs will be:

$$c_D = \left[2\frac{(k+1)\cdot(k+2)\cdot\gamma\cdot c_m^k\cdot f_E}{L}\right]^{\frac{1}{k+2}} \tag{4}$$

The number of organizations active in equilibrium in the region is then given by:

$$N = \frac{2 \cdot (k+1) \cdot \gamma}{\eta} \cdot \frac{\alpha - c_D}{c_D}.$$
(5)

Using reasonable values for parameters<sup>6</sup> (that satisfy the restrictions assumed here and in Melitz & Ottaviano (2008), the relationship between the efficiency distribution shape parameter k and the number of organizations active in equilibrium is illustrated in Figure 4.



Melitz & Ottaviano (2008) derive the average surplus revenues and average organization output. Using these derivations, along with the number of organizations presented in equation 5 and illustrated in Figure 4 we can examine the relation between k and the total surplus revenue earned by all culture producers combined, as well as the total production of cultural goods and services. These are illustrated in Figures 5 and 6, respectively.

Finally, we can solve for the equilibrium value of the utility contribution of culture to the overall level of welfare of the consumers in the region. This will be given by:

$$U = 1 + \frac{\alpha - c_D}{2 \cdot \eta} \cdot \left( \alpha - \frac{k+1}{k+2} \cdot c_D \right)$$
(6)

Given the negative impact of increasing k on the number of organizations and hence the variety of cultural output as well as the total volume of cultural production, it is not surprising that this declines as k increases, as indicated in Figure 7.

When an organization opens in the region, it will be confronted with a range of location options. The location available to the new culture producer will be part of the source of random variation in the costs of

<sup>&</sup>lt;sup>6</sup>The examples take  $f_E = 10000, c_M = 10000, L = 100000, \gamma = 10, \alpha = 5000, \eta = 1.1$  but qualitatively are not sensitive to these values as long as other restrictions apply.

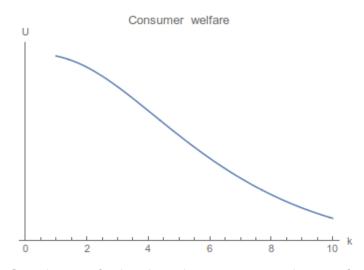


Figure 7: Contribution of cultural goods to consumer utility as a function of k

production. If culture producers in the region are clustered together so that they can share inputs, find labour matches in common pools, and in other ways learn from each other or benefit from proximity to one another then their costs will tend to be lower. If the region is one where locations available to culture producers are more dispersed and isolated, then their costs will tend to be higher. We use the parameter k to capture these impacts of available agglomeration or location within culture concentrations.

If the extent of agglomeration in the area determines the distribution of costs that culture producers may experience, it is natural to assume that the shape parameter k depends on the extent of culture concentration. In section 2 we introduced measures that provided an index of relative concentration  $\lambda$ , the number of peaks in the density of distances  $\rho$ , the median distance between organizations  $\theta$ , the maximum gap  $\delta$  between the density of distances between culture producers and the  $95^{th}$  percentile of densities of distances between other nonprofits, and the distance scale  $\theta_{\delta}$  where this gap occurs.

We assume that  $k = k(\lambda, \rho, \theta, \delta, \theta_{\delta})$ , and if agglomeration economies are important for culture producers would would further expect that:

$$k_{\lambda} < 0 \Rightarrow$$
 concentration implies lower costs (7)

$$k_o < 0 \Rightarrow$$
 more "peaks" implies lower costs (8)

These expectations follow from the relatively unambiguous nature of the measures  $\lambda$  and  $\rho$ . An increase of  $\lambda$  from zero to one is a clear indication that at some level culture producers are more concentrated than other similar organizations. An increase in  $\rho$  may be a signal that there are a larger number of local concentrations of

culture producers, and this increases the chance that a potential producer will find a location near one of them. If an increase in the median distance between culture producers  $\theta$  occurs by a uniform increase in the distance between every organization, then we might also expect:

$$k_{\theta} > 0 \Rightarrow$$
 greater distance between organizations implies higher costs (9)

Finally, the impact of the maximum difference between the density of culture producers and the density of similar organizations might indicate more options for agglomeration economies if the difference is associated with a distance scale at which agglomeration economies are active. An increase in the distance at which this occurs could indicate the presence of distinct clusters separated by that distance or simply greater dispersion. These observations may be summarized as:

$$k_{\delta} \leq 0 \Rightarrow$$
 greater gap between culture and other densities has an ambiguous impact (10)  
 $k_{\theta_{\delta}} \leq 0 \Rightarrow$  greater distance at which the maximum gap occurs has an ambiguous impact. (11)

These expected impacts are not simply a matter of "intuition" applied to the culture sector. They are the implication of the adapted model of market size and productivity, coupled with the hypothesis that agglomeration economies will shift the distribution of marginal production costs to lower expected costs for producers who can locate in concentrations.

In the next section we report on the results of calculating each of the concentration measures for all urban areas in the United States for the years 1989 through 2009. We then proceed to estimate models that will put some of these expectations to the test.

#### 4 Data and initial measurement

The data used for analysis are obtained from the Core Financial Files for 501(c)(3) Public Charities available from the National Center for Charitable Statistics (NCCS). The data are more fully described in Pedroni & Sheppard (2013*a*) and Pedroni & Sheppard (2013*b*), and in a guide to their use published by the Center NCCS (2006). A panel of data have been assembled that cover the years 1989 through 2009, providing location and financial information on more than 40,000 nonprofit organizations engaged in the production, performance, display or promotion of cultural activities. In addition to the cultural non-profits, information on all other nonprofits were obtained from the same source since these will be used as the basis for comparison with the patterns of location of cultural nonprofits, as indicated in the example presented in Section 3.

Considerable preparation was required for the data to be usable. Errors and inaccuracies occur in large databases such as this, and where possible corrections were made to locations. In rare cases the IRS form 990 filing for an organization does not appear in the database for a particular year, but does appear for adjacent years so that it is clear that the organization did not cease to operate nor did it fall below the filing threshold. In such cases values for expenditures and revenues were interpolated in an effort to make a complete panel. The instances where this occurs are few.

Each organization was located and assigned a latitude and longitude. For most of the organizations, this was done based on the extended zip code ('zip+4') which is available for virtually all organizations. For a smaller number locations were determined by geocoding street addresses. Based on these locations, all organizations are located within one of the 384 urban areas (Metropolitan Areas and Metropolitan Area Divisions) following the definitions put forward by the Office of Managment and Budget in OMB (2009). For the final analysis not all urban areas had sufficient data to permit analysis. Most of the results presented below make actual use of between 372 and 381 urban areas. With organizations located and the data arranged, we proceeded to calculate, for each MSA or MSA Division, the median distance, cluster, significant peaks, maximum difference or gap, and the distance or separation at which the maximum gap occurs. This was done for all cities for each of the 21 years for which data were available.

Variable	Obs	$\mu$	$\sigma$	Min	Max
GDP per capita	7875	30631.36	7462.84	12517.97	68809.21
Total surplus	7873	7.02	22.11	-126.28	882.72
Total arts expenditures	7873	36.62	50.33	0.16	715.16
Unemployment	7875	5.65	2.64	1.24	31.12
heta – median distance	7724	8.50	7.37	0.01	54.70
$\lambda$ – cluster	7724	0.63	0.48	0	1
ho – signif peaks	7724	2.06	3.33	0	38
$\delta$ – maximum gap	7724	0.03	0.08	0	1.05
$ heta_\delta$ – distance at max gap	7724	17.80	24.32	0	172.43
N – cultural nonprofits	7724	58.13	137.41	3	2507
All nonprofits	7724	523.38	1007.20	15	14094
MSA width in km	7724	73.92	48.69	0.57	365.70

Table 1:	Descriptive	statistics	for	1989-2009

Summary statistics limited to data for the year 2009 are presented in the Appendix in Table 5. The Appendix also contains a complete set of these cluster variables for every individual city, presented as Table 6. Descriptive statistics for the combined set of observations covering all 21 years are presented in Table 1. In this and all

tables, distance measures are always in kilometers, and all prices are adjusted for inflation and presented in 2000 dollars.

The descriptive statistics presented in Table 1 reveal at least a few facts about the structure of culture concentrations in the US during the 21 years from 1989 through 2009. We can see that on average across the sample, the median distance between cultural organizations within the same urban area is 8.5 kilometers, and that across MSAs this ranges from approximately 100 meters to nearly 55 kilometers. About 63 percent of the cities and years exhibit 'clustering' as defined above, and analysis of the distribution of densities reveals a little over 2 significant peaks. There are on average more than 58 cultural organizations in US urban areas, and more than 523 nonprofits of all types.

## 5 Agglomeration and the number of culture providers

One of the predictions of the model presented in section 3 is that an increase in the cost distribution parameter k will result in a decrease in the number of active culture producers, holding other factors constant. In this section we present a direct test of this.

The analysis presented endeavours to hold other factors constant in at least three ways. First, we include a control for the level of real GDP *per capita*, whose change over time or across cities might alter the level of demand for cultural goods as well as the cost of producing them. Second, we employ a fixed-effects estimation method, clustering standard errors by MSA so that any unobserved factors that differ across urban areas but are constant during the 21 years for which the panel data are available will be corrected for. Finally, since the impact on culture producers is for a region with fixed population (L in the discussion of section 3) the analyis uses the number of arts organizations per million residents as the dependent variable.

Table 2 presents the results of these fixed-effects estimations for 6 different models of *per capita* numbers of culture producers, as a function of the measures of culture concentration and real GDP. The essential difference between the 6 models is the set of concentration measures included in the model, with model 6 being the most complete. All models indicate that increases in real GDP *per capita* is associated with increases in the number of culture producers. This association is estimated with precision in all models.

Focusing attention on Model 6, we see that in addition to the impact of real GDP, the index  $\lambda$  that indicates whether the culture producers are concentrated and the number of significant peaks  $\rho$  are also associated with increases in the number of culture producers, as would be predicted by equations 7 and 8. These effects are also estimated with reasonable precision. The impact of median distance between cultural organizations works in the direction suggested by equation 9, with an increase in the median separation associated with a decrease in the numbers of organizations that would be expected if it increases expected marginal costs. The impact, however, is modest in magnitude and not estimated with sufficient precision for us to be confident that the true impact is not zero.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Real GDP	0.0043***	0.0043***	0.0042***	0.0042***	0.0042***	0.0042***
$\sigma$	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002
$\lambda$ - Clustered	1.6129	1.5536	0.9462	0.8667	2.8866**	3.3705**
$\sigma$	1.074	1.080	1.088	1.095	1.353	1.368
ho - Peaks			0.9523***	0.9541***	0.9694***	1.0077***
$\sigma$			0.218	0.218	0.216	0.223
$\delta$ - Max gap						-12.1167
$\sigma$						11.910
$ heta_\delta$ - Max gap dist					0.0666***	0.0685***
$\sigma$					0.021	0.021
heta - Med distance		-0.0472		-0.0623	-0.0969	-0.1308
$\sigma$		0.145		0.144	0.146	0.147
Constant	-41.4420***	-41.1362***	-40.4463***	-40.0410***	-41.4028***	-41.1761***
$\sigma$	6.134	6.063	6.075	6.001	5.955	5.961
$\sigma_u$	51.1159	51.1072	51.1708	51.1527	51.0861	51.1774
$\sigma_e$	17.3009	17.3015	17.1890	17.1892	17.1657	17.1548
ρ	0.8972	0.8972	0.8986	0.8985	0.8985	0.8990
within	0.4814	0.4815	0.4882	0.4882	0.4897	0.4904
between	0.1106	0.1109	0.1103	0.1107	0.1124	0.111
overall	0.1573	0.1576	0.1575	0.1579	0.1593	0.1578
F statistic	244.59***	166.81***	168.25***	128.71***	107.76***	90.39***
Correlation $u_i$	-0.1712	-0.1712	-0.1754	-0.175	-0.1735	-0.178
Obs	7724	7724	7724	7724	7724	7724
Groups	375	375	375	375	375	375

Table 2:	Fixed-effects	models of a	arts organizations	per million	residents.	1989-2009
					,	

\*\*\* - significant at 1%, \*\* - significant at 5%, \* - significant at 10%

The impacts of the variables  $\delta$  and  $\theta_{\delta}$  are mixed, with increases in  $\delta$  associated with decreases in the number of organizations and increases in  $\theta_{\delta}$  associated with increases in the number of culture producers. This first is not estimated with precision but the second is statistically significant. Since the prediction of the model presented in equations 10 and 11 is itself dependent on the context, these cannot be interpreted as adding or detracting from the confidence we have in the analysis presented above. The first three results, however, and in particular the first two estimated impacts of  $\lambda$  and  $\rho$ , can be said to be consistent with the predictions of the model and providing at least tentative support for an analysis that views culture producers through a lens inspired by the model of Melitz & Ottaviano (2008) coupled with a maintained hypothesis that the distribution of the costs of culture production are shifted lower when producers are concentrated.

#### 6 Cultural concentration and economic prosperity

A question posed in Section 1 was whether there was a clear economic benefit available to urban areas resulting from encouraging the clustering or concentration of cultural nonprofits. To the extent that we are willing to accept an answer based purely on theory, the question has been addressed in section 3. Concentration of culture production leads to reduced levels of k. This leads to an increase in total production of culture as shown in Figure 6. This increase in culture production is associated with an increase in consumer well-being as implied by equation 6 and illustrated in Figure 7

There are multiple channels, however, through which increases in local culture production might improve the well-being of local residents. In addition to the mechanisms related to market size and productivity outlined in section 3 there may be direct impacts on worker productivity that take place either by attracting more productive individuals to reside in the urban area or by directly augmenting the human capital of those in residence.

To explore this effect we examine the relationship between total local culture production (as approximated by the total expenditures of cultural organizations *per capita*) and the measures of culture concentration introduced and used above on the real GDP *per capita* in each urban area. Again we utilize a fixed-effects estimation procedure applied to our panel of 375 urban areas over 21 years, and include a control for local unemployment rates to control for transitory macroeconomic shocks, underutilized productive capacity and economic distress in the individual urban areas. Once again, we cluster standard errors by MSA. The results are presented in Table 3. Again the analysis is presented in the form of estimates for 6 different models whose main difference is the set of measures of concentration of culture production included. Model 6 is the most complete so let us concentrate discussion on that model.

Table 3 reveals a strong positive association between *per capita* arts production in the urban area and *per capita* real GDP. This may reflect both the general positive relationship between culture production and consumer well-being identified above as well as some other channel of influence such as direct augmentation of worker productivity. Of more direct interest for our analysis is whether, beyond this impact of total arts

production, there is some impact that results from the concentration of culture production. Model 6 reveals that there is. Urban areas with  $\lambda = 1$ , in which culture production is regarded as clustered, are associated with levels of *per capita* GDP that are more that \$1660 greater than those whose culture production is not clustered. Increases in the number  $\rho$  of significant peaks in the distribution of distances between culture producers are also associated with increases in *per capita* GDP.

In this analysis an increase in the median distance  $\theta$  between cultural organizations is also associated with an increase in real GDP *per capita*. An increase from New York's 4 kilometers to Los Angeles's 20 would, all else equal, be associated with an increase of more than \$1850 in *per capita* GDP. We speculate that this latter result is not due to increased efficiency or increased culture production (which in any event is separately controlled for) but rather to an alternative channel in which increased values of  $\theta$  has the consequence of making cultural organizations more accessible to residents of the urban area.

Increases in the maximum difference  $\delta$  between the density of distances between cultural organizations and the density of distances between other organizations, as well as the distance where this maximum difference occurs exhibits an impact not unlike that observed above. Increase in the distance  $\theta_{\delta}$  are associated with increases in *per capita* GDP and increases in the difference itself are associated with decreases, but the latter impact is estimated with such low precision that it is not statistically significant. Overall, it must be said that the analysis is consistent with a maintained hypothesis that organizing culture producers into clusters, where agglomeration economies might magnify their impact, is associated with improvements in the local economy.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Arts Production	101.045***	97.065***	94.924***	92.420***	91.343***	91.350***
$\sigma$	16.15	15.81	15.77	15.54	15.58	15.57
Unemployment		-383.794***	-397.648***	-395.486***	-387.715***	-387.479***
$\sigma$		36.80	36.74	36.15	36.23	36.19
$\lambda$ - Clustered	1167.869***	1114.713***	1264.261***	1097.418***	1676.737***	1660.580***
$\sigma$	203.76	196.04	196.22	191.58	245.00	251.27
heta - Med distance			130.640***	125.780***	114.814***	115.925***
$\sigma$			36.99	36.35	35.98	36.79
ho - Peaks				203.366***	206.592***	205.304***
$\sigma$				37.56	37.72	37.89
$ heta_\delta$ - Max gap dist					19.356***	19.295***
$\sigma$					5.25	5.27
$\delta$ - Max gap						403.386
$\sigma$						1367.18
Constant	26317.73***	28648.55***	27602.42***	27410.81***	26786.89***	26776.72***
σ	596.11	683.76	715.29	695.74	677.82	677.03
$\sigma_u$	5840.736	5668.916	5700.577	5654.583	5649.998	5654.439
$\sigma_e$	3461.538	3405.180	3385.704	3359.191	3348.696	3348.855
ρ	0.740	0.735	0.739	0.739	0.740	0.740
within	0.207	0.233	0.242	0.254	0.259	0.259
between	0.242	0.274	0.270	0.280	0.282	0.281
overall	0.223	0.254	0.253	0.264	0.266	0.266
F	42.36***	86.84***	78.21***	70.63***	65.68***	56.26***
Correlation $u_i$	-0.3033	-0.2777	-0.2837	-0.2811	-0.2808	-0.2814
Obs	7724	7724	7724	7724	7724	7724
Groups	375	375	375	375	375	375

Table 3: Fixed-effects models of real GDP per capita, 1989-2009

\*\*\* - significant at 1%, \*\* - significant at 5%, \* - significant at 10%

One objection that might be made concerning the analysis presented in Table 3 is that of reverse causality. It might be said that an increase in arts production (or its spatial arrangement) does not increase local economic output, but rather that more prosperous local economies are better-positioned to support and patronize local culture producers. The latter is in some sense almost certainly true, and sorting out the relative direction of causality is a central focus of recent analysis presented in Pedroni & Sheppard (2013*a*) and Pedroni & Sheppard (2013*b*). Their analysis used the same data, and the presence of a co-integrating relationship between total culture production and *per capita* GDP, to estimate an error correction model whose 'speed of adjustment' parameters can serve as the basis for a test of the existence and direction of causality. Their analysis found that causality ran in **both** directions: shocks in *per capita* GDP generate long run increases in culture production and shocks in *per capita* culture production generate long run changes in *per capita* GDP. This provides some justification for the models presented in Table 3.

As a final investigation into the importance of culture concentrations, we will examine the influence of selected variables measuring concentration of cultural nonprofits on the 'speed of adjustment' ratios from the error correction models estimated and presented in Pedroni & Sheppard (2013*a*). The median value across all urban areas of these ratios is the basis for the test of the causal connection between expenditures by cultural nonprofits and local economic prosperity. These ratios, in aggregate, provide a valid test of the 'creative economy' channel for local prosperity that has been widely discussed. If the median of these ratios is positive, then an increase in *per capita* cultural expenditure by all cultural nonprofits in the city will cause an increase in *per capita* GDP that is persistent in the long run. We will present some tests of the impact of clustering and other factors on this ratio.

How is this median, and hence the tests of causal connection, affected by cultural concentration? Table 4 presents the results of quantile-regression estimation of the impact of the indicated variables on the median of the ratio of speed-of-adjustment parameters from the estimated error-correction models. Any factor that increases the value of this median value increases our confidence of the causal link that would justify public policy in support of cultural organizations.

The results of the quantile regression models are not always estimated with sufficient precision to permit us to be very confident that the true impacts are not zero, but all estimates of relevant parameters are positive. Urban areas with clustered cultural non-profits are associated with higher median speed-of-adjustment ratios, and for the simpler models we can be very confident of this result. Cities with higher median distance are also associated with higher ratios, and this is true of larger population and greater levels of affluence as well. This suggests that in the set of urban areas with culture concentrations, we can be more confident that there is a

Variable	Model 1	Model 2	Model 3	Model 4
cluster	0.0722 **	0.0760**	0.0416	0.0424
$\sigma$	0.036	0.036	0.037	0.039
median distance		0.0029	0.0009	0.0019
σ		0.002	0.002	0.002
population			0.0320**	0.0273**
$\sigma$			0.013	0.014
GDP				0.0031
$\sigma$				0.002
constant	0.0445 *	0.0155	0.0355	-0.0667
σ	0.026	0.030	0.030	0.067
pseudo $R^2$	0.0018	0.0024	0.0042	0.005
observations	372	372	372	372

Table 4: Quantile regression analysis of causality ratios

\*\*\* - significant at 1%, \*\* - significant at 5%, \* - significant at 10%

clear causal link in which changes to culture production generate long run increases in local economic well-being.

To put these results in perspective, it is worth remembering that the median speed-of-adjustment ratio for all cities presented in Pedroni & Sheppard (2013a) was 0.07, with a bootstrapped standard deviation of 0.03, so adding 0.04 to 0.07 to this level, as suggested by the parameter estimate for the variable cluster, is a significant strengthening of the inference of a causal connection.

### 7 Conclusions and directions for future research

In this paper we have laid out some approaches for the formal analysis of culture concentrations. We have presented a model and examples that provide basic insights into the economic forces that affect the density, concentration and clustering of cultural nonprofits. We have identified appropriate data for measurement and analysis of cultural nonprofits in US urban areas, collected these data and used them to calculate the measures over 21 years in 375 urban areas. We have then proceeded to assemble these calculations together with other data into a panel data set and test the impact of cultural concentration on some economic outcomes. In particular, we look at the impact on *per capita* GDP in cities and on *per capita* surplus of cultural nonprofits in the city.

We find some strong and potentially important results, and some results that are intriguing if imprecise. Having local cultural nonprofits that are clustered (more dense than all nonprofits) is associated with greater *per capita* GDP, but so is increasing the median distance between organizations. In addition to these results, increasing the number of significant peaks in the density function - generally associated with more distinct clusters - is associated with greater *per capita* GDP. Combined, this suggests that the spatial structure for cultural nonprofits most conducive to a positive economic impact would be one with several clusters, scattered widely over the urban area.

In addition to this, the analysis presented results that reinforce the maintained hypothesis that agglomeration economies are an important force affecting culture production. Urban areas with higher measures of culture concentration are associated with increased numbers of arts organizations *per capita*, as predicted by the theoretical model presented. This suggests that encouraging such spatial structure can increase total culture production and consumer welfare in cities. Like all statistical analysis, these results must be regarded as provisional. Further investigations of this type in other settings would be very helpful for policy makers who are confronted with a very large number of requests for very limited available funds. Research to explore the relationship between culture production, and the spatial structure of culture production, could enhance the efficiency of allocation of these scarce funds.

# References

- Billings, S. B. & Johnson, E. B. (2014), Agglomeration within an urban area. University of North Carolina, Charlotte working paper.
- Duranton, G. & Overman, H. G. (2005), 'Testing for localization using micro-geographic data.', *Review of Economic Studies* **72**(4), 1077 1106.
- Duranton, G. & Overman, H. G. (2008), 'Exploring the detailed location patterns of U.K. manufacturing industries using microgeographic data.', *Journal of Regional Science* **48**(1), 213 243.
- Florida, R. (2002), The Rise of the Creative Class, Basic Books, New York, NY.
- Lorenzen, M. & Frederiksen, L. (2008), Why do Cultural Industries Cluster? Localization, Urbanization, Products and Projects, Edward Elgar, Cheltenham and Northampton, pp. 155–179.
- Markusen, A. & Johnson, A. (2006), Artists centers: Evolution and impact on careers, neighborhoods and economies, Technical report, University of Minnesota, Humphrey Institute of Public Affairs, Minneapolis, MN.
- Melitz, M. J. & Ottaviano, G. I. P. (2008), 'Market size, trade, and productivity', *Review of Economic Studies* **75**, 295–316.
- NASAA (2012), State cultural districts, Technical report, National Assembly of State Arts Agencies, Washington, D.C. 20005.
- NCCS (2006), Guide to using NCCS data, Technical report, National Center for Charitable Statistics, Urban Institute, Washington, DC.
- OMB (2009), Update of statistical area definitions and guidance on their uses, Technical report, Executive Office of the President, Office of Management and Budget, Washington, DC 20503.
- Pedroni, P. & Sheppard, S. (2013*a*), Culture shocks and consequences: the connection between the arts and economic growth. Williams College Working Paper.
- Pedroni, P. & Sheppard, S. (2013b), The Economic Consequences of Cultural Organizations, Brookings Institution Press, chapter 9.

- Rosenthal, S. S. & Strange, W. C. (2001), 'The determinants of agglomeration', *Journal of Urban Economics* **50**, 191–229.
- Stern, M. J. & Seifert, S. C. (2009), Cultivating "natural" cultural districts, Technical report, Social Impact of the Arts Project, Philadelphia, PA.
- Stern, M. J. & Seifert, S. C. (2010), 'Cultural clusters: The implications of cultural assets agglomeration for neighborhood revitalization', *Journal of Planning Education and Research* **29**(3), 262–279.

# 8 Appendix

Variable	$\mu$	$\sigma$	Min	Max
$\theta$ - Median distance	9.31	8.08	0	55
$\lambda$ - Cluster	0.68	0.47	0	1
$\delta$ - Density max gap	0.05	0.10	0.0002	1.0492
$ heta_\delta$ - Max gap distance	0.05	0.10	0.0002	1.0492
ho - Significant peaks	2.41	3.55	0	20
N - $#$ Arts orgs	74.70	168.88	3	2404
# Nonprofits	683.53	1260.33	50	13754
MSA width	75.86	48.99	4.2866	365.7

Table 5: Descriptive statistics for cluster variables, 2009

Urban Area	Median distance	Cluster	Density max gap	Max gap distance	Signif. peaks	# Arts orgs	# Non- profits	MSA width
Abilene, TX	4.35	0	0.0000	0.00	0	15	135	55
Akron, OH	9.62	1	0.0329	0.03	12	64	666	64
Albany, GA	5.78	0	0.0000	0.00	0	8	101	39
Albany-Schenectady-Troy, NY	13.24	1	0.0174	0.02	9	124	1274	129
Albuquerque, NM	6.38	1	0.0176	0.02	2	116	928	68
Alexandria, LA	4.96	0	0.0000	0.00	0	9	86	14
Allentown-Bethlehem-Easton, PA-NJ	14.25	1	0.0223	0.02	6	95	764	129
Altoona, PA	1.76	0	0.0000	0.00	0	12	135	28
Amarillo, TX	3.70	0	0.0000	0.00	0	13	162	94
Ames, IA	6.37	0	0.0246	0.02	2	16	124	32
Anchorage, AK	11.11	1	0.0133	0.01	1	75	641	141
Anderson, IN	1.79	1	0.3031	0.30	1	10	84	16
Anderson, SC	12.37	0	0.0000	0.00	0	10	86	37
Ann Arbor, MI	5.20	1	0.0610	0.06	6	76	539	51
Anniston-Oxford, AL	0.62	1	0.1979	0.20	1	9	84	27
Appleton, WI	1.45	1	0.0819	0.08	0	17	198	62
Asheville, NC	9.08	1	0.1403	0.14	3	70	552	82
Athens-Clarke County, GA	6.69	1	0.0935	0.09	2	16	197	43
Atlanta-Sandy Springs-Marietta, GA	16.00	1	0.0085	0.01	3	359	4601	185
Atlantic City-Hammonton, NJ	10.40	1	0.0339	0.03	8	21	271	63
Auburn-Opelika, AL	8.92	0	0.0125	0.01	1	10	100	47
Augusta-Richmond County, GA-SC	12.88	1	0.0215	0.02	1	45	374	96
Austin-Round Rock, TX	5.12	1	0.0382	0.04	2	229	1874	109
Bakersfield, CA	48.97	0	0.0218	0.02	11	34	437	207
Baltimore-Towson, MD	16.16	1	0.0085	0.01	14	291	2982	128
Bangor, ME	10.54	1	0.0643	0.06	4	12	210	122
Barnstable Town, MA	25.94	1	0.0032	0.00	2	93	484	80

10.14

26.11

8.20

8.78

0.0072

0.0005

0.0000

0.0000

0.01

0.00

0.00

0.00

Continued on next page

Baton Rouge, LA

Battle Creek, MI

Beaumont-Port Arthur, TX

Bay City, MI

	Median		Density	Max gap	Signif.	# Arts	# Non-	MSA
Urban Area	distance	Cluster	max gap	distance	peaks	orgs	profits	width
Bellingham, WA	0.63	1	0.1959	0.20	0	31	263	81
Bend, OR	1.22	0	0.0000	0.00	0	20	239	52
Bethesda-Frederick-Rockville, MD	10.79	0	0.0019	0.00	1	177	1885	81
Billings, MT	7.24	1	0.0050	0.01	10	20	201	115
Binghamton, NY	13.14	1	0.0062	0.01	1	27	242	88
Birmingham-Hoover, AL	8.49	1	0.0042	0.00	2	104	999	135
Bismarck, ND	1.14	0	0.0000	0.00	0	20	192	73
Blacksburg-Christiansburg-Radford, VA	3.36	0	0.0000	0.00	0	19	161	71
Bloomington, IN	4.16	1	0.0104	0.01	1	31	226	88
Bloomington-Normal, IL	1.53	1	0.0779	0.08	1	23	183	33
Boise City-Nampa, ID	8.50	1	0.0344	0.03	12	53	531	120
Boston-Quincy, MA	9.17	1	0.0064	0.01	8	397	3389	106
Boulder, CO	9.44	1	0.0154	0.02	8	84	614	55
Bowling Green, KY	0.33	0	0.0000	0.00	0	14	113	22
Bradenton-Sarasota-Venice, FL	6.06	1	0.0618	0.06	10	80	616	59
Bremerton-Silverdale, WA	10.43	1	0.0210	0.02	0	37	283	46
Bridgeport-Stamford-Norwalk, CT	15.60	1	0.0087	0.01	8	177	1515	62
Brownsville-Harlingen, TX	16.65	1	0.0067	0.01	0	19	152	66
Brunswick, GA	6.25	1	0.0100	0.01	0	10	97	72
Buffalo-Niagara Falls, NY	9.46	1	0.0076	0.01	1	133	1169	67
Burlington, NC	9.47	1	0.0016	0.00	0	8	126	27
Burlington-South Burlington, VT	10.67	1	0.0043	0.00	2	55	420	80
Cambridge-Newton-Framingham, MA	13.65	1	0.0077	0.01	4	389	2709	87
Camden, NJ	13.45	1	0.0078	0.01	6	90	1121	101
Canton-Massillon, OH	5.14	1	0.1234	0.12	7	32	384	55
Cape Coral-Fort Myers, FL	7.36	0	0.0311	0.03	8	42	405	72
Cape Girardeau-Jackson, MO-IL	10.75	0	0.0003	0.00	0	8	97	51
Carson City, NV	2.07	0	0.0000	0.00	0	12	75	5
Casper, WY	0.45	0	0.0185	0.02	0	13	126	15
Cedar Rapids, IA	1.75	1	0.0227	0.02	4	27	232	111
Champaign-Urbana, IL	6.72	1	0.0052	0.01	0	28	255	61
Charleston, WV	1.09	1	0.1126	0.11	2	38	318	139
Charleston-North Charleston-Summerville, SC	7.78	1	0.0563	0.06	12	56	537	124

	Median		Density	Max gap	Signif.	# Arts	# Non-	MSA
Urban Area	distance	Cluster	max gap	distance	peaks	orgs	profits	width
Charlotte-Gastonia-Concord, NC-SC	12.69	1	0.0318	0.03	12	119	1416	147
Charlottesville, VA	3.49	1	0.0728	0.07	1	50	401	111
Chattanooga, TN-GA	7.43	1	0.0065	0.01	1	40	473	63
Cheyenne, WY	0.56	0	0.0053	0.01	20	17	139	72
Chicago-Naperville-Joliet, IL	15.78	1	0.0157	0.02	6	882	7634	134
Chico, CA	16.26	0	0.0000	0.00	0	24	227	47
Cincinnati-Middletown, OH-KY-IN	12.24	1	0.0116	0.01	1	206	2153	130
Clarksville, TN-KY	10.79	0	0.0000	0.00	0	10	115	60
Cleveland, TN	0.00		0.0000	0.00				0
Cleveland-Elyria-Mentor, OH	18.26	1	0.0025	0.00	10	266	2364	145
Coeur d'Alene, ID	1.51	1	0.0813	0.08	1	8	116	24
College Station-Bryan, TX	2.78	0	0.0000	0.00	0	12	134	44
Colorado Springs, CO	6.14	1	0.0142	0.01	4	77	809	130
Columbia, MO	2.88	1	0.0356	0.04	0	32	246	61
Columbia, SC	8.33	1	0.0709	0.07	3	61	704	132
Columbus, GA-AL	2.58	1	0.1006	0.10	0	19	213	41
Columbus, IN	4.28	0	0.0187	0.02	0	9	100	20
Columbus, OH	12.93	1	0.0069	0.01	9	209	2369	117
Corpus Christi, TX	1.35	1	0.0794	0.08	1	29	274	86
Corvallis, OR	2.45	0	0.0000	0.00	0	16	160	16
Cumberland, MD-WV	19.44	0	0.0000	0.00	0	8	86	47
Dallas-Plano-Irving, TX	11.12	1	0.0083	0.01	2	356	3360	157
Dalton, GA	1.35	0	0.0000	0.00	0	6	78	29
Danville, IL	3.74	0	0.0000	0.00	0	9	54	8
Danville, VA	6.49	1	0.0003	0.00	0	13	110	49
Davenport-Moline-Rock Island, IA-IL	6.36	1	0.0326	0.03	1	57	427	101
Dayton, OH	7.91	1	0.0079	0.01	7	92	775	84
Decatur, AL	3.51	0	0.0000	0.00	0	6	84	64
Decatur, IL	3.01	1	0.0053	0.01	0	12	104	21
Deltona-Daytona Beach-Ormond Beach, FL	9.32	0	0.0031	0.00	0	28	275	51
Denver-Aurora-Broomfield, CO	9.88	1	0.0051	0.01	8	308	3135	209
Des Moines-West Des Moines, IA	6.02	1	0.0287	0.03	3	68	791	128
Detroit-Livonia-Dearborn, MI	17.42	0	0.0028	0.00	6	131	1344	65

145	Median		Density	Max gap	Signif.	# Arts	# Non-	MSA
Urban Area	distance	Cluster	max gap	distance	peaks	orgs	profits	width
Dothan, AL	3.00	0	0.0000	0.00	0	5	58	29
Dover, DE	3.51	1	0.0082	0.01	0	16	128	37
Dubuque, IA	1.97	1	0.0194	0.02	0	12	135	50
Duluth, MN-WI	29.52	1	0.0293	0.03	6	49	417	125
Durham-Chapel Hill, NC	9.34	1	0.0194	0.02	1	89	777	70
Eau Claire, WI	9.53	1	0.0004	0.00	0	17	171	48
Edison-New Brunswick, NJ	24.47	1	0.0024	0.00	3	208	2546	91
El Centro, CA	9.20	0	0.0000	0.00	0	5	68	84
Elizabethtown, KY	10.63	0	0.0000	0.00	0	8	72	28
Elkhart-Goshen, IN	14.69	0	0.0002	0.00	0	10	187	30
Elmira, NY	2.53	0	0.0000	0.00	0	9	81	5
El Paso, TX	6.65	1	0.0289	0.03	1	30	341	47
Erie, PA	3.03	1	0.1400	0.14	3	26	308	77
Eugene-Springfield, OR	4.57	1	0.0008	0.00	0	59	444	194
Evansville, IN-KY	2.33	1	0.0517	0.05	1	35	382	74
Fairbanks, AK	3.53	1	0.0221	0.02	1	20	170	75
Fargo, ND-MN	3.56	1	0.0014	0.00	0	27	249	57
Farmington, NM	8.65	1	0.0016	0.00	0	5	78	85
Fayetteville, NC	7.15	0	0.0000	0.00	0	18	156	48
Fayetteville-Springdale-Rogers, AR-MO	6.47	1	0.0162	0.02	1	29	334	91
Flagstaff, AZ	5.30	1	0.0089	0.01	0	19	135	169
Flint, MI	4.02	1	0.0330	0.03	1	29	261	37
Florence, SC	11.06	0	0.0068	0.01	1	17	136	44
Florence-Muscle Shoals, AL	3.18	1	0.0021	0.00	0	8	88	31
Fond du Lac, WI	30.79	0	0.0000	0.00	0	9	100	75
Fort Collins-Loveland, CO	5.50	1	0.0180	0.02	1	54	382	70
Fort Lauderdale-Pompano Beach-Deerfield Beach, FL	7.92	1	0.0578	0.06	15	97	1052	36
Fort Smith, AR-OK	5.64	1	0.0328	0.03	2	21	202	144
Fort Walton Beach-Crestview-Destin, FL	1.22	1	0.1093	0.11	1	7	98	31
Fort Wayne, IN	3.77	1	0.0743	0.07	2	50	419	53
Fort Worth-Arlington, TX	13.69	1	0.0176	0.02	4	131	1512	109
Fresno, CA	6.55	1	0.0090	0.01	1	52	589	167
Gadsden, AL	6.14	0	0.0000	0.00	0	4	65	14

	Median		Density	Max gap	Signif.	# Arts	# Non-	MSA
Urban Area	distance	Cluster	max gap	distance	peaks	orgs	profits	width
Gainesville, FL	3.47	1	0.0108	0.01	0	28	330	88
Gainesville, GA	0.00	0	0.0000	0.00	0	10	112	14
Gary, IN	19.88	0	0.0006	0.00	0	34	474	53
Glens Falls, NY	21.70	1	0.0167	0.02	1	25	198	73
Goldsboro, NC	7.29	0	0.0000	0.00	0	9	78	18
Grand Forks, ND-MN	3.85	1	0.0012	0.00	1	16	149	163
Grand Junction, CO	2.54	1	0.0088	0.01	0	13	144	108
Grand Rapids-Wyoming, MI	10.09	1	0.0044	0.00	3	78	888	117
Great Falls, MT	3.17	1	0.0031	0.00	0	16	123	50
Greeley, CO	8.27	1	0.0301	0.03	1	16	157	96
Green Bay, WI	8.42	1	0.0099	0.01	4	31	277	97
Greensboro-High Point, NC	8.83	1	0.0512	0.05	5	61	659	56
Greenville, NC	7.61	0	0.0034	0.00	0	13	141	48
Greenville-Mauldin-Easley, SC	10.18	1	0.0247	0.02	2	51	628	108
Gulfport-Biloxi, MS	15.89	0	0.0015	0.00	2	17	116	81
Hagerstown-Martinsburg, MD-WV	13.26	1	0.0085	0.01	1	28	283	99
Hanford-Corcoran, CA	0.88	0	0.0000	0.00	0	5	61	56
Harrisburg-Carlisle, PA	18.54	1	0.0111	0.01	6	87	798	102
Harrisonburg, VA	8.59	1	0.0142	0.01	0	16	168	44
Hartford-West Hartford-East Hartford, CT	16.78	1	0.0006	0.00	3	209	1698	89
Hattiesburg, MS	14.69	0	0.0000	0.00	0	4	82	41
Hickory-Lenoir-Morganton, NC	16.00	1	0.0142	0.01	1	29	253	73
Holland-Grand Haven, MI	11.13	1	0.0582	0.06	1	21	268	49
Honolulu, HI	4.77	1	0.0232	0.02	1	153	1087	68
Hot Springs, AR	3.33	1	0.0027	0.00	0	16	116	28
Houma-Bayou Cane-Thibodaux, LA	6.39	0	0.0000	0.00	0	10	107	15
Houston-Sugar Land-Baytown, TX	16.52	1	0.0146	0.01	3	416	4024	210
Huntington-Ashland, WV-KY-OH	20.08	1	0.0027	0.00	0	14	221	98
Huntsville, AL	2.88	1	0.0219	0.02	0	33	282	73
Idaho Falls, ID	0.43	1	0.1530	0.15	1	12	81	19
Indianapolis-Carmel, IN	6.70	1	0.0798	0.08	6	187	2101	122
Iowa City, IA	2.78	1	0.0167	0.02	0	25	213	35
Ithaca, NY	0.99	1	0.0075	0.01	0	23	223	42

32

	Median		Density	Max gap	Signif.	# Arts	# Non-	MSA
Urban Area	distance	Cluster	max gap	distance	peaks	orgs	profits	width
Jackson, MI	2.20	1	0.0003	0.00	0	8	89	40
Jackson, MS	4.42	1	0.0618	0.06	3	45	576	80
Jackson, TN	0.51	1	0.1067	0.11	1	9	77	22
Jacksonville, FL	18.36	1	0.0200	0.02	13	94	1044	97
Jacksonville, NC	0.00		0.0000	0.00				0
Janesville, WI	4.20	0	0.0000	0.00	0	16	159	36
Jefferson City, MO	18.42	0	0.0005	0.00	0	18	212	81
Johnson City, TN	8.53	1	0.0007	0.00	0	17	192	64
Johnstown, PA	12.59	0	0.0109	0.01	2	12	161	42
Jonesboro, AR	0.00		0.0000	0.00				0
Joplin, MO	8.87	0	0.0087	0.01	0	12	164	35
Kalamazoo-Portage, MI	3.21	1	0.0260	0.03	5	42	341	102
Kankakee-Bradley, IL	13.80	0	0.0000	0.00	0	4	71	28
Kansas City, MO-KS	12.29	1	0.0495	0.05	3	210	2127	156
Kennewick-Pasco-Richland, WA	14.04	0	0.0029	0.00	1	26	196	74
Killeen-Temple-Fort Hood, TX	44.24	0	0.0016	0.00	0	12	173	120
Kingsport-Bristol-Bristol, TN-VA	36.95	1	0.0323	0.03	9	32	259	138
Kingston, NY	9.61	1	0.0275	0.03	1	41	231	58
Knoxville, TN	9.36	1	0.0766	0.08	7	65	685	66
Kokomo, IN	1.33	0	0.0463	0.05	0	7	67	5
La Crosse, WI-MN	5.15	0	0.0279	0.03	1	16	169	47
Lafayette, IN	5.52	0	0.0000	0.00	0	24	181	117
Lafayette, LA	0.48	1	0.3992	0.40	0	21	231	31
Lake Charles, LA	0.90	0	0.0000	0.00	0	15	118	38
Lake County-Kenosha County, IL-WI	8.61	1	0.0283	0.03	5	60	692	42
Lake Havasu City-Kingman, AZ	38.74	0	0.0000	0.00	0	6	72	78
Lakeland-Winter Haven, FL	15.63	0	0.0018	0.00	0	22	306	60
Lancaster, PA	7.66	1	0.0739	0.07	6	58	588	75
Lansing-East Lansing, MI	6.50	0	0.0000	0.00	0	54	578	92
Laredo, TX	2.16	0	0.0000	0.00	0	8	69	4
Las Cruces, NM	2.72	0	0.0241	0.02	1	15	117	29
Las Vegas-Paradise, NV	13.47	1	0.0022	0.00	6	65	702	171
Lawrence, KS	1.35	1	0.2620	0.26	0	10	154	6

	Median		Density	Max gap	Signif.	# Arts	# Non-	MSA
Urban Area	distance	Cluster	max gap	distance	peaks	orgs	profits	width
Lawton, OK	1.31	1	0.1721	0.17	0	8	69	12
Lebanon, PA	5.07	1	0.2851	0.29	2	13	137	23
Lewiston, ID-WA	4.86	0	0.0000	0.00	0	5	60	10
Lewiston-Auburn, ME	6.02	1	0.0357	0.04	2	10	120	40
Lexington-Fayette, KY	4.81	1	0.0619	0.06	5	62	666	61
Lima, OH	3.07	1	0.0143	0.01	0	10	133	33
Lincoln, NE	2.01	1	0.1250	0.13	1	51	476	64
Little Rock-North Little Rock-Conway, AR	6.96	1	0.0212	0.02	0	49	700	98
Logan, UT-ID	1.68	1	0.0594	0.06	1	12	62	24
Longview, TX	7.97	1	0.0660	0.07	1	13	166	48
Longview, WA	17.49	0	0.0000	0.00	0	4	80	38
Los Angeles-Long Beach-Glendale, CA	19.94	1	0.0043	0.00	5	1081	8581	127
Louisville/Jefferson County, KY-IN	8.04	1	0.0500	0.05	3	113	1099	102
Lubbock, TX	4.22	0	0.0000	0.00	0	23	244	54
Lynchburg, VA	12.60	0	0.0000	0.00	0	32	289	123
Macon, GA	8.59	1	0.0114	0.01	2	22	206	78
Madera-Chowchilla, CA	33.02	0	0.0000	0.00	0	6	67	67
Madison, WI	8.15	1	0.0059	0.01	14	127	1108	129
Manchester-Nashua, NH	9.53	0	0.0676	0.07	3	52	510	76
Manhattan, KS	27.23	0	0.0014	0.00	0	13	148	59
Mankato-North Mankato, MN	3.35	1	0.0051	0.01	0	16	138	47
Mansfield, OH	3.88	1	0.0111	0.01	0	11	111	27
McAllen-Edinburg-Mission, TX	8.29	1	0.0124	0.01	0	25	233	59
Medford, OR	11.35	0	0.3487	0.35	4	45	293	31
Memphis, TN-MS-AR	10.71	1	0.0308	0.03	5	92	1027	113
Merced, CA	3.56	0	0.0000	0.00	0	6	82	21
Miami-Miami Beach-Kendall, FL	8.64	1	0.0076	0.01	6	199	1649	42
Michigan City-La Porte, IN	12.37	0	0.0000	0.00	0	14	102	35
Midland, TX	8.92	0	0.0000	0.00	0	12	143	21
Milwaukee-Waukesha-West Allis, WI	9.95	1	0.0309	0.03	9	205	2116	70
Minneapolis-St. Paul-Bloomington, MN-WI	13.39	1	0.0114	0.01	3	498	4713	213
Missoula, MT	2.11	0	0.0000	0.00	0	34	229	67
Mobile, AL	2.59	1	0.2469	0.25	3	29	308	33

	Median		Density	Max gap	Signif.	# Arts	# Non-	MSA
Urban Area	distance	Cluster	max gap	distance	peaks	orgs	profits	width
Modesto, CA	8.28	1	0.1169	0.12	6	33	314	46
Monroe, LA	4.42	1	0.0012	0.00	0	9	143	40
Monroe, MI	16.42	1	0.0004	0.00	0	5	76	43
Montgomery, AL	7.50	1	0.0225	0.02	1	31	408	106
Morgantown, WV	10.38	1	0.0028	0.00	0	9	150	94
Morristown, TN	0.00	1	1.0492	1.05	0	3	111	52
Mount Vernon-Anacortes, WA	21.08	0	0.0006	0.00	0	19	143	47
Muncie, IN	2.40	1	0.0232	0.02	0	8	108	20
Muskegon-Norton Shores, MI	0.74	1	0.6223	0.62	2	14	140	12
Myrtle Beach-North Myrtle Beach-Conway, SC	14.23	0	0.0061	0.01	2	14	155	43
Napa, CA	13.30	0	0.0180	0.02	1	30	253	46
Naples-Marco Island, FL	7.23	0	0.0000	0.00	0	26	305	48
Nashville-DavidsonMurfreesboroFranklin, TN	9.53	1	0.0177	0.02	1	154	1704	173
Nassau-Suffolk, NY	41.22	0	0.0015	0.00	12	274	2832	201
Newark-Union, NJ-PA	19.98	0	0.0000	0.00	0	253	2694	121
New Haven-Milford, CT	11.95	1	0.0763	0.08	7	108	1183	72
New Orleans-Metairie-Kenner, LA	3.33	1	0.0286	0.03	0	134	1107	106
New York-White Plains-Wayne, NY-NJ	4.39	1	0.0651	0.07	1	2404	13754	112
Niles-Benton Harbor, MI	7.17	0	0.2008	0.20	2	18	149	28
Norwich-New London, CT	14.69	1	0.0256	0.03	3	53	376	64
Oakland-Fremont-Hayward, CA	15.13	1	0.0308	0.03	7	410	3384	92
Ocala, FL	5.61	0	0.0010	0.00	0	9	150	65
Ocean City, NJ	18.30	0	0.0039	0.00	0	26	125	43
Odessa, TX	1.08	0	0.0000	0.00	0	11	84	10
Ogden-Clearfield, UT	6.25	1	0.0308	0.03	1	23	205	27
Oklahoma City, OK	6.63	1	0.0098	0.01	5	123	1129	141
Olympia, WA	2.29	1	0.1194	0.12	1	29	270	58
Omaha-Council Bluffs, NE-IA	12.26	1	0.0301	0.03	4	99	932	156
Orlando-Kissimmee, FL	11.38	1	0.0036	0.00	4	113	1448	103
Oshkosh-Neenah, WI	7.18	0	0.0000	0.00	0	16	183	41
Owensboro, KY	12.62	0	0.0107	0.01	0	11	101	33
Oxnard-Thousand Oaks-Ventura, CA	19.99	1	0.0113	0.01	5	91	784	69
Palm Bay-Melbourne-Titusville, FL	9.35	0	0.0000	0.00	0	32	327	38

	Median		Density	Max gap	Signif.	# Arts	# Non-	MSA
Urban Area	distance	Cluster	max gap	distance	peaks	orgs	profits	width
Palm Coast, FL	2.07	1	0.1921	0.19	1	8	50	24
Panama City-Lynn Haven-Panama City Beach, FL	0.73	0	0.0000	0.00	0	5	78	32
Parkersburg-Marietta-Vienna, WV-OH	6.29	1	0.0065	0.01	0	19	148	53
Pascagoula, MS	16.26	0	0.0000	0.00	0	8	64	33
Peabody, MA	18.58	1	0.0036	0.00	5	127	1056	64
Pensacola-Ferry Pass-Brent, FL	3.27	1	0.2804	0.28	7	23	286	35
Peoria, IL	7.67	1	0.0116	0.01	2	24	312	75
Philadelphia, PA	13.39	1	0.0253	0.03	5	576	4922	131
Phoenix-Mesa-Scottsdale, AZ	15.36	1	0.0021	0.00	14	254	2668	244
Pine Bluff, AR	0.00		0.0000	0.00				0
Pittsburgh, PA	17.17	1	0.0051	0.01	15	249	2786	156
Pittsfield, MA	13.99	1	0.0192	0.02	4	65	320	54
Pocatello, ID	1.13	0	0.0000	0.00	0	5	56	48
Portland-South Portland-Biddeford, ME	33.40	1	0.0018	0.00	9	120	963	137
Portland-Vancouver-Beaverton, OR-WA	10.11	1	0.0170	0.02	2	311	2860	214
Port St. Lucie, FL	7.36	1	0.1265	0.13	5	22	267	36
Poughkeepsie-Newburgh-Middletown, NY	23.57	1	0.0097	0.01	6	83	665	130
Prescott, AZ	48.57	1	0.0241	0.02	1	22	212	110
Providence-New Bedford-Fall River, RI-MA	19.59	1	0.0063	0.01	12	255	2033	108
Provo-Orem, UT	8.99	0	0.0000	0.00	0	18	202	52
Pueblo, CO	1.85	1	0.1796	0.18	1	16	142	47
Punta Gorda, FL	0.74	1	0.0795	0.08	0	12	85	32
Racine, WI	1.74	1	0.0569	0.06	1	15	197	55
Raleigh-Cary, NC	7.30	1	0.0591	0.06	6	120	1327	93
Rapid City, SD	0.26	0	0.0000	0.00	0	24	153	34
Reading, PA	11.13	1	0.0113	0.01	4	49	329	74
Redding, CA	4.59	0	0.0000	0.00	0	13	186	58
Reno-Sparks, NV	7.22	1	0.0879	0.09	16	49	379	102
Richmond, VA	10.16	1	0.0052	0.01	0	136	1398	161
Riverside-San Bernardino-Ontario, CA	54.70	1	0.0040	0.00	10	170	2096	366
Roanoke, VA	4.40	1	0.0695	0.07	2	42	395	56
Rochester, MN	6.91	1	0.0410	0.04	3	26	235	63
Rochester, NY	15.33	1	0.0035	0.00	2	133	1108	177

	Median		Density	Max gap	Signif.	# Arts	# Non-	MSA
Urban Area	distance	Cluster	max gap	distance	peaks	orgs	profits	width
Rockford, IL	6.62	1	0.0738	0.07	3	30	271	35
Rockingham County-Strafford County, NH	15.09	1	0.0597	0.06	9	56	501	77
Rocky Mount, NC	34.01	0	0.0014	0.00	0	9	88	74
Rome, GA	1.24	0	0.0000	0.00	0	9	71	8
SacramentoArden-ArcadeRoseville, CA	23.65	1	0.0043	0.00	6	191	2150	231
Saginaw-Saginaw Township North, MI	3.05	1	0.1216	0.12	0	14	126	49
St. Cloud, MN	19.29	1	0.0070	0.01	1	21	182	117
St. George, UT	17.32	0	0.0023	0.00	0	12	68	76
St. Joseph, MO-KS	3.32	0	0.0000	0.00	0	15	118	106
St. Louis, MO-IL	16.01	1	0.0048	0.00	4	270	2712	254
Salem, OR	6.32	1	0.0129	0.01	5	46	403	89
Salinas, CA	4.55	1	0.0312	0.03	4	68	441	116
Salisbury, MD	8.32	0	0.0017	0.00	0	12	114	17
Salt Lake City, UT	8.05	1	0.0081	0.01	12	111	1046	114
San Angelo, TX	2.49	0	0.0000	0.00	0	10	119	14
San Antonio, TX	11.64	1	0.0163	0.02	3	155	1520	148
San Diego-Carlsbad-San Marcos, CA	16.78	1	0.0128	0.01	16	327	2861	133
Sandusky, OH	1.86	0	0.0285	0.03	0	11	93	40
San Francisco-San Mateo-Redwood City, CA	6.41	1	0.0359	0.04	1	599	3737	102
San Jose-Sunnyvale-Santa Clara, CA	14.09	1	0.0054	0.01	3	258	1985	94
San Luis Obispo-Paso Robles, CA	14.58	1	0.0932	0.09	2	47	371	88
Santa Ana-Anaheim-Irvine, CA	13.72	1	0.0043	0.00	2	234	2880	62
Santa Barbara-Santa Maria-Goleta, CA	18.25	1	0.0159	0.02	0	98	658	110
Santa Cruz-Watsonville, CA	5.54	1	0.0551	0.06	10	52	443	54
Santa Fe, NM	1.13	1	0.2204	0.22	0	101	390	29
Santa Rosa-Petaluma, CA	17.87	1	0.0030	0.00	1	84	721	84
Savannah, GA	4.09	0	0.0000	0.00	0	34	267	74
ScrantonWilkes-Barre, PA	15.86	1	0.0172	0.02	0	39	472	81
Seattle-Bellevue-Everett, WA	13.12	1	0.0178	0.02	6	483	3700	98
Sebastian-Vero Beach, FL	2.91	1	0.0338	0.03	1	15	126	27
Sheboygan, WI	1.37	0	0.0656	0.07	1	12	120	44
Sherman-Denison, TX	3.62	0	0.0000	0.00	0	7	89	58
Shreveport-Bossier City, LA	1.33	1	0.3537	0.35	1	27	261	42

	Median		Density	Max gap	Signif.	# Arts	# Non-	MSA
Urban Area	distance	Cluster	max gap	distance	peaks	orgs	profits	width
Sioux City, IA-NE-SD	0.00	1	0.0708	0.07	1	20	170	126
Sioux Falls, SD	1.39	1	0.0187	0.02	0	23	307	89
South Bend-Mishawaka, IN-MI	3.14	1	0.1926	0.19	5	27	315	57
Spartanburg, SC	1.02	1	0.2272	0.23	1	13	181	33
Spokane, WA	3.35	1	0.1508	0.15	3	37	447	61
Springfield, IL	2.25	1	0.1730	0.17	5	32	320	41
Springfield, MA	13.05	0	0.0023	0.00	5	128	927	92
Springfield, MO	3.52	1	0.0140	0.01	3	26	380	90
Springfield, OH	2.39	1	0.1241	0.12	7	13	143	43
State College, PA	4.54	1	0.0037	0.00	1	25	183	72
Stockton, CA	11.87	1	0.0069	0.01	0	30	374	58
Sumter, SC	7.50	0	0.0000	0.00	0	7	76	16
Syracuse, NY	19.54	1	0.0191	0.02	13	78	821	108
Tacoma, WA	10.63	1	0.0456	0.05	6	60	874	97
Tallahassee, FL	6.03	0	0.0054	0.01	6	52	524	85
Tampa-St. Petersburg-Clearwater, FL	17.38	1	0.0269	0.03	7	141	1875	79
Terre Haute, IN	1.15	1	0.0348	0.03	0	13	155	37
Texarkana, TX-Texarkana, AR	0.70	1	0.3207	0.32	1	5	90	45
Toledo, OH	10.96	1	0.0021	0.00	2	57	678	174
Topeka, KS	4.76	0	0.0000	0.00	0	25	239	86
Trenton-Ewing, NJ	6.04	1	0.0500	0.05	8	89	779	37
Tucson, AZ	5.75	1	0.0175	0.02	0	100	843	244
Tulsa, OK	7.51	0	0.0000	0.00	0	65	888	159
Tuscaloosa, AL	2.46	1	0.0580	0.06	3	17	159	63
Tyler, TX	3.40	0	0.0000	0.00	0	13	216	33
Utica-Rome, NY	15.48	1	0.0018	0.00	1	27	279	98
Valdosta, GA	4.65	0	0.0000	0.00	0	6	79	59
Vallejo-Fairfield, CA	17.27	0	0.0013	0.00	0	40	296	40
Victoria, TX	1.24	1	0.0268	0.03	0	18	111	53
Vineland-Millville-Bridgeton, NJ	19.69	1	0.2414	0.24	3	21	145	42
Virginia Beach-Norfolk-Newport News, VA-NC	21.95	1	0.0167	0.02	6	146	1384	133
Visalia-Porterville, CA	6.95	1	0.0034	0.00	1	25	255	74
Waco, TX	3.46	1	0.0017	0.00	0	21	240	37

	Median		Density	Max gap	Signif.	# Arts	# Non-	MSA
Urban Area	distance	Cluster	max gap	distance	peaks	orgs	profits	width
Warner Robins, GA	8.23	0	0.0000	0.00	0	4	55	17
Warren-Troy-Farmington Hills, MI	23.13	1	0.0014	0.00	1	176	1778	184
Washington-Arlington-Alexandria, DC-VA-MD-WV	15.43	1	0.0009	0.00	2	837	8362	196
Waterloo-Cedar Falls, IA	1.58	1	0.5020	0.50	1	18	179	50
Wausau, WI	3.92	1	0.0131	0.01	0	13	124	45
Weirton-Steubenville, WV-OH	15.22	0	0.0000	0.00	0	4	105	31
Wenatchee-East Wenatchee, WA	6.80	0	0.0056	0.01	0	15	111	39
West Palm Beach-Boca Raton-Boynton Beach, FL	6.06	1	0.0073	0.01	5	112	1135	77
Wheeling, WV-OH	9.19	1	0.0024	0.00	0	12	144	69
Wichita, KS	6.25	1	0.0167	0.02	1	50	539	88
Wichita Falls, TX	0.76	1	0.0099	0.01	0	9	142	98
Williamsport, PA	20.53	0	0.0000	0.00	0	13	134	6
Wilmington, DE-MD-NJ	11.93	1	0.0068	0.01	0	104	902	108
Wilmington, NC	5.74	1	0.0359	0.04	2	31	289	9
Winchester, VA-WV	5.06	1	0.0077	0.01	0	17	125	92
Winston-Salem, NC	6.59	1	0.0516	0.05	3	48	520	84
Worcester, MA	15.36	1	0.0016	0.00	1	83	872	85
Yakima, WA	16.81	1	0.0010	0.00	0	14	185	112
York-Hanover, PA	9.28	1	0.0127	0.01	1	27	386	60
Youngstown-Warren-Boardman, OH-PA	12.52	1	0.0084	0.01	2	40	490	99
Yuba City, CA	10.51	0	0.0000	0.00	0	6	80	49
Yuma, AZ	5.05	1	0.0006	0.00	0	10	81	43