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Culture Concentrations:

the spatial structure of arts nonprofits

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Abstract

This paper presents some approaches for analysis of culture concentrations. The paper proposes several measures of such concentrations, and calculates them for cultural nonprofits in US urban areas from 1989 to 2009. These measures are then used to explore the impact of cultural concentration on economic outcomes.

The paper finds 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 distinct clusters appears to be associated with greater *per capita* GDP. Combining these observations, it appears 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.

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 neighborhoods and cultural cities has come from those with academic, public policy, commercial and aesthetic interests in the arts.[1]

At present in the United States, there are 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.[2] These designated cultural districts provide a variety of benefits, ranging from simple recognition of the neighborhood 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 goal 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 what are often called agglomeration economies. These improvements in efficiency that come about when organizations doing similar things are located close to one another have been of interest to economists 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 and enabling them to produce higher quality experiences for their audiences and patrons.

Similar tensions can 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. Alternatively, many 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

[1] See, for example, Lorenzen & Frederiksen (2008) and Stern & Seifert (2010).

[2] See the report by the National Association of State Arts Agencies NASAA (2012).

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 their neighborhood.

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 understood. The goal of this paper is to make a modest contribution toward such understanding.

2 How to measure clustering of organizations

Which factors affect the concentration of cultural organizations, and how can we measure and compare these concentrations 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 good 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 neighborhoods. 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 data and 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 neighborhood. Despite these 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 and display within the city, county, or other arbitrarily drawn area is vulnerable to this criticism.

We present an alternative that tries to address 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 present in this section a very simple model that relates market parameters to the equilibrium density of nonprofit organizations. We then explore some examples of how to measure and analyze the structure that emerges from this simple model. We proceed to identify a group of measures that can be applied to a large number of cities.

Consider an organization operating to produce cultural services in a setting where other organizations producing similar services are free to enter. 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 can be modeled as seeking to serve the largest possible audience, 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.

The requirement of economic sustainability, along with some very simple assumptions about the structure of patron or audience frequency of attendance and the costs of producing the cultural services, permits us to understand the equilibrium density of such organizations. In order to model the simple outlines of this process, consider a world where for each organization (and hence each cultural production type) each household will attend a concert, exhibition or other production a fixed number of times per year, and combining this rate of audience attendance with the local density of population will provide a value d for the number of visitors or audience members per kilometer (or other unit of distance) as we move through the urban area. [3]

Travel is costly both in terms of time and of actual expense. It is therefore natural in this simple exposition to assume that households always patronize the organization that offers the lowest combination of admission price and travel costs. The cost of travel for each person is assumed to be a constant of t per unit distance, so that if an admission price of p is being charged by the cultural organization, the effective price to a person who resides distance x from the organization is $p + t \cdot x$.

Suppose that initially the organizations are spread out, with a distance of R separating each. In equilibrium, entry of cultural organizations takes place so that R is reduced to the minimum amount consistent with economic sustainability of the organizations. Suppose that the neighboring cultural organization has chosen an admission or ticket price of $p_0 \geq 0$. Then the distance b that defines the boundary between the audience area of the cultural organization and its neighbor is defined by the distance b where the admission plus travel cost of attending the two organizations is equal:

$$p + t \cdot b = p_0 + t \cdot (R - b) \tag{1}$$

which implies that

$$b = \frac{p_0 - p + R \cdot t}{2 \cdot t}. \tag{2}$$

The value b given in equation 2 identifies the maximum extent of the potential audience for the cultural organization. In a setting where there are similar neighboring organizations on both sides of the organization, the cultural organization will serve an area of width $2 \cdot b$. Using this we can solve for admission price

[3] For example, a report from the Office of Research & Analysis at the NEA (2007) indicates that 9.3 percent of adults attend at least one classical music concert each year, while 22.7 percent make at least one visit to an art museum. Population density per kilometer in a relatively dense US urban setting would be on the order of 300 to 400 adults, so that each kilometer along a street in a US urban setting could generate 30 symphony ticket sales or 80 visits to the art museum each year. These levels of density are observed in major cities like Boston or Chicago. In less dense places the appropriate value of d may be lower.

p that, if applied, will generate total annual audience q for the organization:

$$p(q) = (p_0 + R \cdot t) - \frac{t}{d} \cdot q. \tag{3}$$

In economic terms, the cultural organization in this setting faces a simple linear demand curve with slope equal to $-\frac{t}{d}$ and maximum price of $(p_0 + R \cdot t)$. If the organization were trying to maximize total revenues from admissions, it would set $p = \frac{1}{2}(p_0 + R \cdot t)$ and if the goal was to maximize surplus revenue or profit it would set an admission price even higher than this. In the case at hand, however, the organization operates as a nonprofit seeking to maximize the audience served while covering its costs, and to determine that behavior we need to define the costs of operation.

To illustrate the outcome of a very simple cost structure, consider a situation where the total costs of operating the cultural organization consists of a fixed component f that does not vary with the audience size and a variable component that is proportional to the size of the audience served. Let the cost per audience member be represented by m. For an annual audience of q the total costs of producing the programming for the season are given by:

$$c(q) = f + m \cdot q \tag{4}$$

Then the average cost of production is:

$$ac(q) = m + \frac{f}{q} \tag{5}$$

A cultural nonprofit seeking to serve the largest audience possible will set price so that $p(q) = ac(q)$. Apart from the need to be economically sustainable, there is no limit to the number of cultural nonprofits of a particular type that can exist in a city.

The past two decades have seen significant growth in the number of cultural nonprofits throughout the US, and while this has generated concerns about donor fatigue in some settings it also has generated organizations that present a wider range of artists and serve many communities that were previously overlooked. As new organizations enter the market, they and the existing ones can be thought of as squeezing closer together - operating with smaller markets but continuing to pursue the same overall goal of providing a cultural experience for the largest possible audience subject to the constraint of being able to cover the costs of production. As new organizations enter, the audience that is available to existing organizations gradually diminishes.

The situation is illustrated in the example presented in Figure 1. Initially, the spacing between organizations is larger, and the choice by the nonprofit is to set a price of admission slightly above 20 and achieve an audience of nearly 200 thousand. In this setting, it is possible for new cultural organizations to open and be economically sustainable. As they do, they crowd the available audience in the urban area and the audience that can be generated at any given admission price shifts down. Eventually, a long-run equilibrium is reached where the typical organization is just sustainable, with an admission price of approximately 32 and an annual attendance of just over 125 thousand.

This is an equilibrium because it is not possible for another organization producing this cultural experience to enter the urban area and be sustainable. A new organization would shift the demand down, and there would then be no combination of price and audience available to existing organizations where price would equal average costs, so it would be impossible to cover the costs of operation.

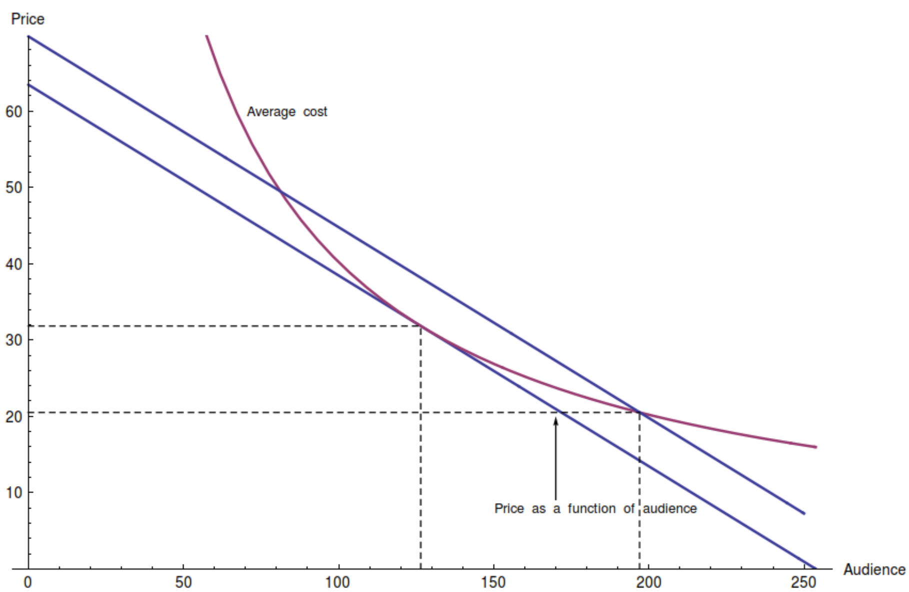

Figure 1: Demand and average cost tangent in equilibrium

The simple algebra of this model allows us to solve for the long-run equilibrium price p, annual audience Q and width of area served R as a function of the parameters providing the density of demand d, the fixed cost f, marginal cost m and transportation costs t:

$$p = m + \sqrt{\frac{f \cdot t}{d}} \tag{6}$$

$$Q = \sqrt{\frac{f \cdot d}{t}} \tag{7}$$

$$R = \sqrt{\frac{f}{d \cdot t}} \tag{8}$$

Thus an increase in fixed costs for cultural organizations implies an increase in the equilibrium admission price, total audience and area served. An increase in the marginal costs increases the admission price but leaves other values unchanged. An increase in the density of demand lowers equilibrium price and results in smaller areas served for each organization, while increasing the total audience. An increase in transportation costs increases the equilibrium admission price, while lowering the size of the area served and total audience. These results are summarized in Table 1.

Table 1: Qualitative impact of a change in costs and demand density

		An increase in:			
	Variable	m	f	t	d
	p	↑	↑	↑	↓
Generates:	Q	–	↑	↓	↑
	R	–	↑	↓	↓

This simple model provides one way of understanding an important source of variation in the density of cultural organizations. The density increases with fixed costs, and decreases with transportation costs and the density of demand for the cultural activity. While the model includes none of the usual *agglomeration economies* that are usually offered as explanations for why clusters of cultural organizations exist, this approach can produce clusters that occur naturally due to differences in the density of demand for various cultural activities and differences in the fixed costs of producing the cultural experiences.

Consider an example with three types of cultural organization. One with relatively high fixed costs and (perhaps as a consequence of the resulting higher admission prices) reduced frequency of annual attendance. We might think of this as typical major art museums with expensive collections and the associated curatorial expenses of presenting important exhibitions. Only the largest cities can accommodate more than two or three such organizations. An intermediate cultural organization has lower fixed costs and slightly higher density of demand. These might represent theaters and performing arts centers. Finally a third category with still lower fixed costs and an increased frequency of attendance. These might be typical of special interest museums, or dance and performing arts centers whose programming targets a specific population or cultural interest. Figure 2 illustrates the equilibrium pattern of locations of cultural organizations in this hypothetical city.[4]

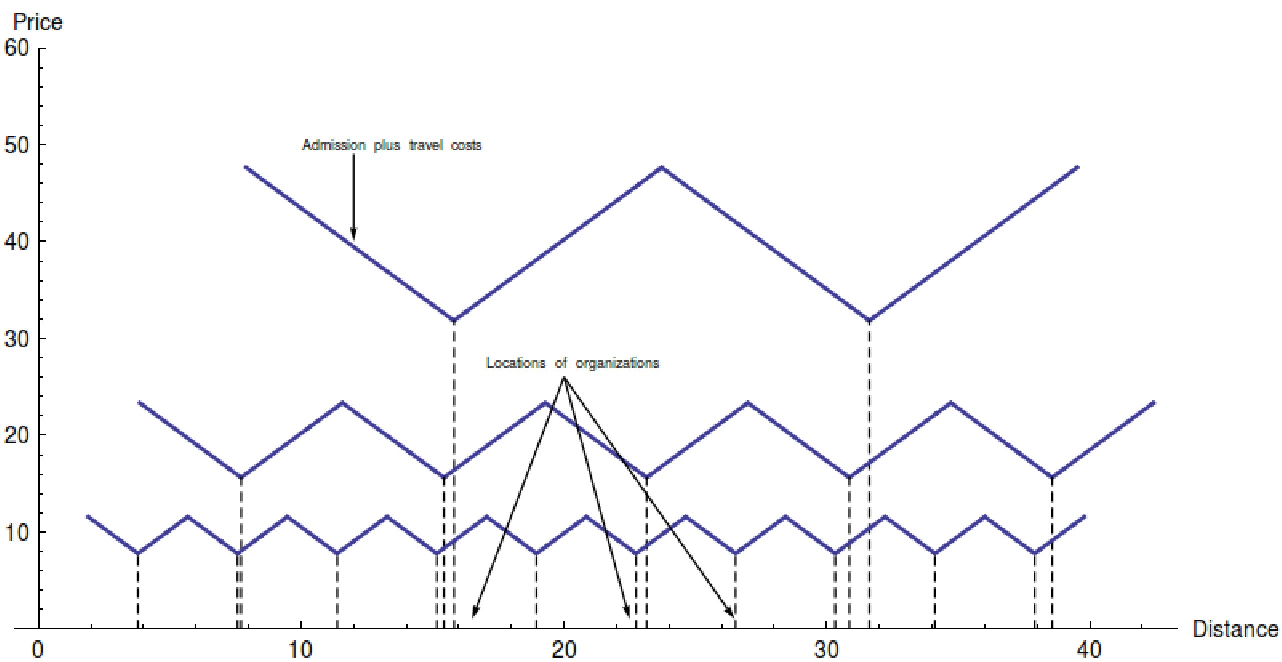

Figure 2: Equilibrium location patterns for three types of cultural organizations

The solid lines indicate the effective attendance price (admission price plus travel costs) for visitors to each type of cultural organization. At the location of the organization, this price is the admission price charged by the organization and a dashed line extends down to the horizontal axis to indicate the location of the organization. There are a few clusters of organizations that appear. Between 15 and 16 kilometers from the (arbitrarily set) origin, there is a grouping that consists of one of each type of organization. Another such cluster - although somewhat lower in density - exists around 31 kilometers. There are smaller clusters consisting of two organizations at 8, 18 and 38 kilometers. All of these 'natural' clusters arise due to the frequency of the respective organizations in long run equilibrium, not due to cost savings or other factors that, if introduced into the model, would result in even more clustering between organizations.

How can we devise a measurement of the clustering of these organizations? It is apparent from the example illustrated in Figure 2 that we cannot use the equilibrium spacing R between organizations of

[4]The three examples were created with three different levels of fixed costs f and demand density d. The marginal costs m and the transportation costs t are the same for all three organization types. Letting subscripts of 1, 2 and 3 denote the largest, intermediate, and smallest organizations the example is contstructed with $f_1 = 4000$, $f_2 = 1000$, and $f_3 = 250$. For demand density, the example uses $d_1 = 8$, $d_2 = 8.4$, and $d_3 = 8.7$.

a particular types. While factors that reduce R do diminish the expected distance between cultural organizations, that is only part of the story. The variety of organizations and the variance in fixed costs and demand density also play a role. In actual cities factors not included in this simple model - like agglomeration economies - may also be important. To study this it would be helpful to find a strategy for measurement that can be widely applied and captures the essential features of interest.

A central component of our interest in the topic is the potential for collaboration and partnerships between cultural organizations, and for relationships to develop that enhance the artistic quality of their production or reduce their costs. These relationships could develop between any pair of organizations in a city. Suppose we consider all pairs of organizations. In the example illustrated in Figure 2 there are 17 organizations resulting in 136 different pairs or potential partnerships. We could ask what the *median* distance between these partners would be, and use that measure as an indicator of the expected difficulty of forming such a relationship. If the median distance is η, then the odds are even that a randomly chosen partner for an organization will be closer than η. Cities with higher values of η might be expected to have less frequently formed partnerships. The distribution of distances for the example illustrated in Figure 2 is presented in Figure 3.

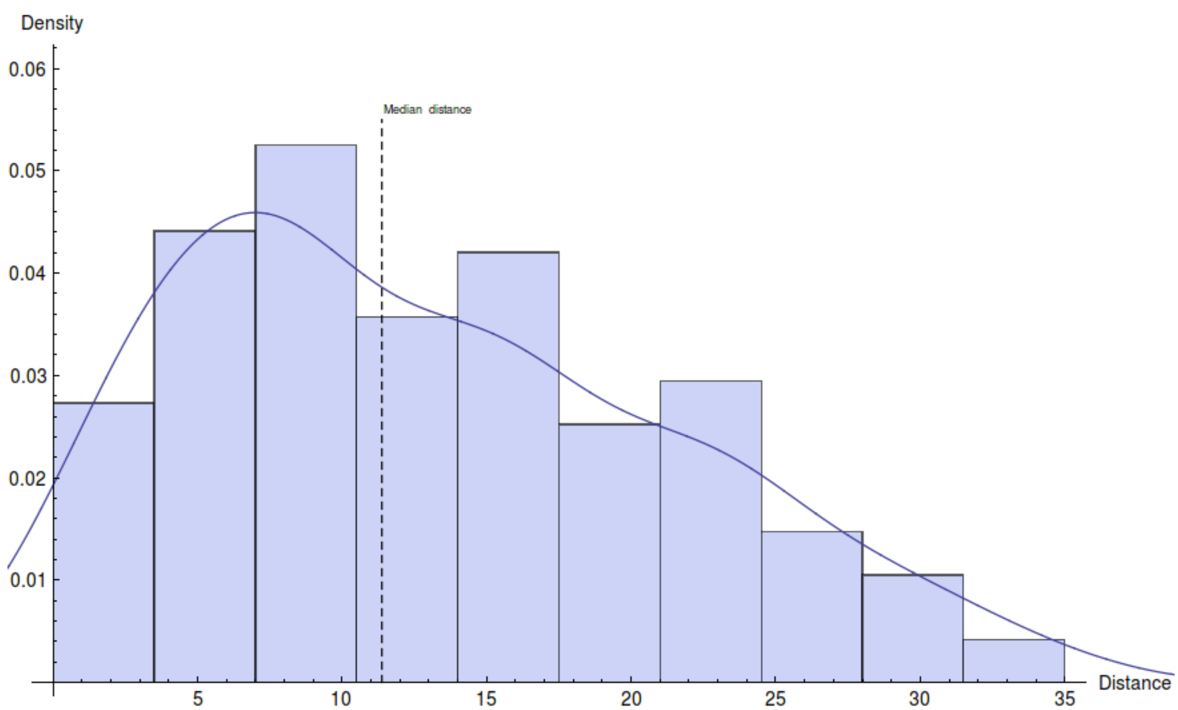

Figure 3: Distribution of distances between cultural organizations

The furthest separation of about 34 kilometers arises between the organization located just under 4 kilometers from the origin and the one located just past 38. The closest organizations are within the clusters and are separated by only a few hundred meters. The distribution is shown both as a histogram and a smoothed approximation to the probability distribution of the observed distances between the 136 pairs of organizations. As indicated, the median distance between organizations is $\eta = 11.37$, so if a collaborative relationship develops between a random pair of cultural organizations in this (simulated) area, the odds are 50 : 50 that they will be separated by 11.37 kilometers or less.

The example shown in Figures 2 and 3 illustrates the potential value of the distribution of distances between all cultural organizations in a city, and the median of this distribution as an approach to understand, compare and potentially even test for the existence of clusters of cultural organizations. It is worth emphasizing again that the clustering that emerges in the example is not the result of building in an incentive for clustering or policy to encourage it.

Whether it is better to call the clusters that do occur *natural* or *accidental* depends on what one expected to occur. Such expectations are generally based on experience in actual cities and from looking at the location patterns of other nonprofit organizations. The next development is to consider how the concentration of cultural nonprofits compares to the concentration of other nonprofit organizations. This is inspired by the analysis of industrial location first presented by Duranton & Overman (2005) and applied by them to analyze the location of manufacturing in Britain in Duranton & Overman (2008). The approach has since been applied to describe and analyze location and the effects of policies in a variety of settings.

The essential idea is to compare the distribution of distances between organizations with the distribution of distances between some reference set of locations. In this paper, we compare the distribution of distances between cultural nonprofits with the distribution of distances between all other nonprofit organizations within each metropolitan area. The distribution of distances between organizations in a given area depends on the number of such organizations. In order to construct a valid comparison, the approach draws repeated random samples of size equal to the number of cultural nonprofits in the city. An approximation to the distribution of distances called the *kernel density* estimate 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.

If the density of cultural nonprofits rises above the 95^{th} percentile of the density distributions of all nonprofits at a distance less than half of the maxmimum distance between nonprofits in the city, we say that the cultural nonprofits are *clustered*. In addition, we provide counts of the number of distinct distances where the density for cultural nonprofits rises above the 95^{th} percentile of distributions for all nonprofits. This number of *significant peaks* provides information about the number of distinct cultural clusters in the urban area. The distance (if any) where the density of cultural nonprofits exceeds the 95^{th} percentile density of all nonprofits is calculated to provide a measure of the scale of the most common or most important cultural clusters, and the numerical difference between the 95^{th} percentile density for all nonprofits and the density of cultural nonprofits provides a measure of the dominance or importance of clusters with this scale.

Figure 4 provides three examples that illustrate these measures. In each of the maps, the locations of other nonprofits are indicated by the + symbols, and the illustrative locations of cultural nonprofits are represented by the ⚑ 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.

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. They exhibit less 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^{th} and lower 5^{th} percentiles of the distribution of distances between other nonprofits. The two vertical lines show the median and 95^{th} 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.

The second example we see clear signs of clusters. 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^{th} 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.

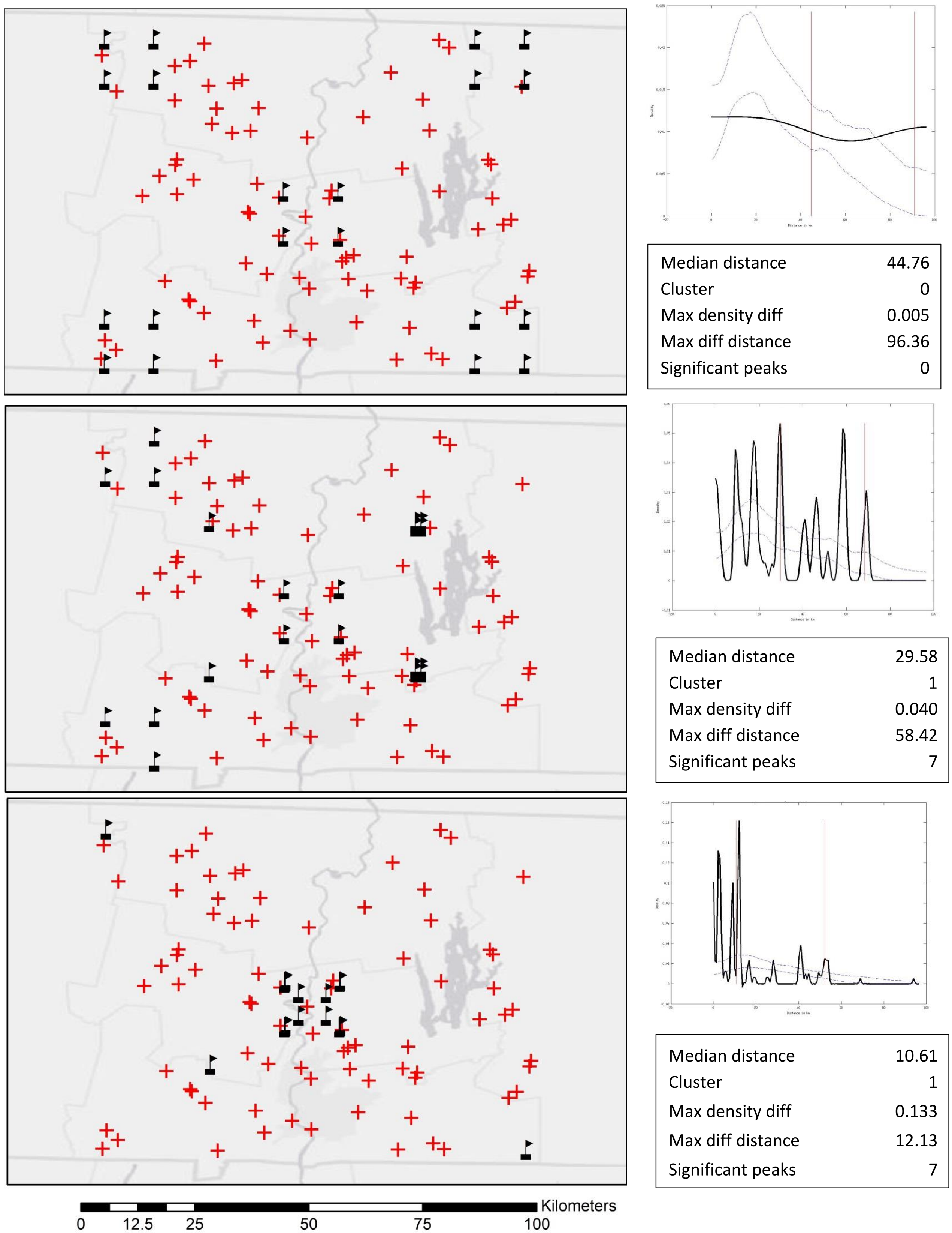

Figure 4: Three illustrations of comparative cluster measurement

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 analyze the distribution of nonprofits in an urban area and note a significant peak in the distribution at some separation distance δ. What this means is that if we took a card and cut a circle of diameter δ 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 'neighborhood' 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 clustered 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 summary, this section has introduced a simple model of equilibrium location choice for nonprofit organizations, and derived the relation between equilibrium spacing between organizations and the demand for the cultural experience and the costs of transportation and production of culture. We have shown by example that in such a model clusters of nonprofit organizations can arise depending on the distribution of these costs and demand across organization types. We identified ways of measuring and analyzing these clusters that focus on the distribution of the distances between pairs of nonprofit organizations. With a series of examples, we have shown the value of five different measures of clustering or agglomeration of cultural nonprofits:

1. The median distance between cultural nonprofits;

2. A dichotomous cluster indicator variable that indicates whether at some scale cultural nonprofits are more clustered than all nonprofits;

3. The number of significant peaks - distinct distances at which the density of cultural nonprofits exceeds the 95^{th} percentile of the density on all nonprofits;

4. The maximum difference between the density of cultural nonprofits and the 95^{th} percentile of the density on all nonprofits;

5. The distance of separation between organizations at which this maximum separation occurs.

All of these measures are based on micro-geographic data about the location of organizations, and 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 difficult or impossible.

In the next section we report on the results of calculating each of these measures for all major urban areas in the United States for the years 1989 through 2009, describing the differences and trends that characterize concentrations of culture in US cities.

3 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), 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 2.

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.

Summary statistics for the 2009 data are presented in the Appendix in Table 6. The Appendix also contains a complete set of these cluster variables for every individual city, presented as Table 7. Descriptive statistics for the combined set of observations covering all 21 years are presented in Table 2. In this and all tables, distance measures are always in kilometers, and all prices are adjusted for inflation and presented in 2000 dollars.

Table 2: Descriptive statistics for 1989-2009

Variable	Obs	μ	σ	Min	Max
gdp per capita	7875	30631.36	7462.84	12517.97	68809.21
arts surplus	7873	7.02	22.11	-126.28	882.72
arts expenditures	7873	36.62	50.33	0.16	715.16
unemployment	7875	5.65	2.64	1.24	31.12
median distance	7724	8.50	7.37	-0.01	54.70
cluster	7724	0.63	0.48	0	1
signif peaks	7724	2.06	3.33	0	38
maximum gap	7724	0.03	0.08	0	1.05
distance at max gap	7724	17.80	24.32	-0.01	172.43
cultural nonprofits	7724	58.13	137.41	3	2507
all nonprofits	7724	523.38	1007.20	15	14094
MSA width	7724	73.92	48.69	0.57	365.70

A table of statistics such as Table 2 conveys some information of its own. We can see that on average across the sample, *per capita* GDP exceeds $30 thousand, 63 percent of the cities and years exhibit 'clustering' as defined above, and the 'width' of an MSA (the maximum observed distance between two nonprofits located in the urban area) averages almost 74 kilometers. These and other facts are presented, but it is difficult when looking at these statistics, especially those with which we are unfamiliar, and know what to make of them.

In order to develop an intuitive feeling for these measures, it can be helpful to make some comparisons between cities with which we might have some familiarity. Towards that end, consider Figure 5, 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.[5] 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.

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 compares well with the common understanding of these two large and important cities. New York cultural organizations are very 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.

[5] The vertical line on the right represents the 95^{th} percentile of separation distances between cultural nonprofits.

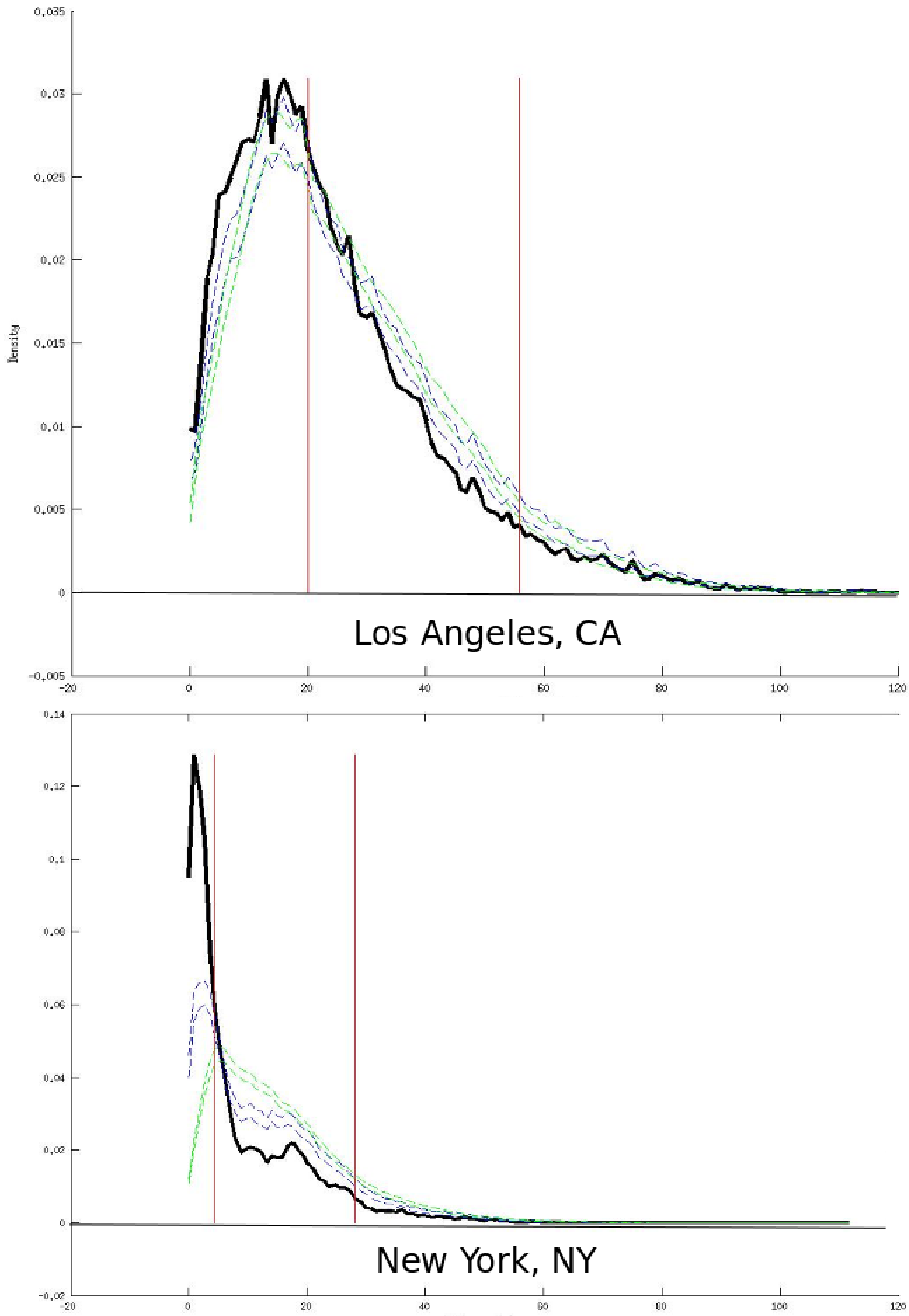

Figure 5: Comparative analysis of Los Angeles and New York City in 2009

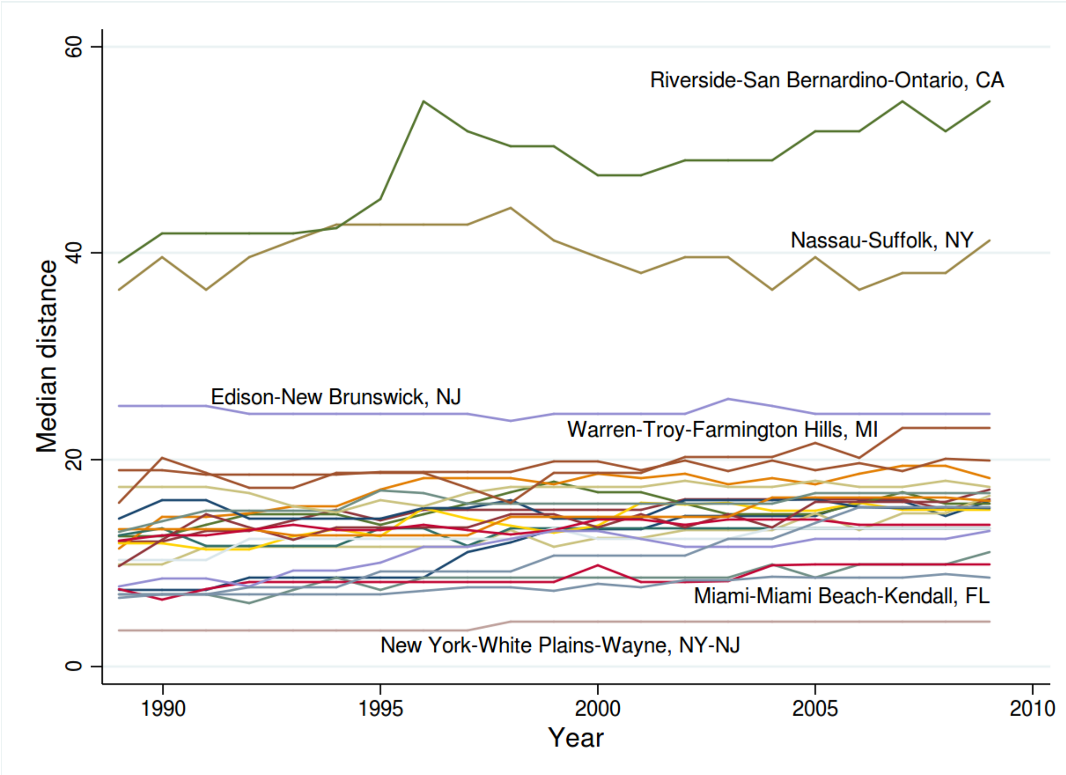

Figure 6: Changes in median distance for largest MSAs, 1989-2009

How do the variables change over time? Figure 6 presents a graph of the time series of the median distance variable from 1989 through 2009, for the 25 cities in the panel with the largest average population levels. Six individual urban areas are labeled. New York the most populous urban area in the panel, also has the lowest median distance between cultural nonprofits. While it is the lowest, the median distance has slightly increased over time - taking a jump in the late 1990s.

Riverside-San Bernardino-Ontario, California is (by this measure at least) the most dispersed large city in the panel, and during the 21 years for which we have data it has become less concentrated, with median distance increasing from just over 39 kilometers in 1989 to almost 55 kilometers in 2009. Nassau-Suffolk, New York and Edison-Brunswick, New Jersey, which are, like Riverside, metropolitan areas with a predominantly suburban feel, are also very dispersed but have been more stable over the time period covered by the panel. Edison-New Brunswick has actually become slightly more concentrated.

Looking at the data graphed in the figure, there are no obvious cyclical effects. This matches our expectations. The spatial structure of nonprofit location would not be expected to swing with the business cycle. We expect it to be relatively stable. In some cities there can be clear patterns of change as new organizations are formed (or grow large enough to be required to file a Form 990) and a few choose new locations. Generally, however, we expect a pattern of very gradual change that plays out over decades. This is precisely why we need a long panel covering a period of 20 or more years in order to be able to analyze the impacts of clustering on the local economy and on the prosperity and sustainability of the organizations themselves. In the next two sections we turn our attention to these questions.

4 Cultural concentration and economic prosperity

A question we 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. Using the measures of clustering introduced above, and having calculated these for each city in each year, we undertake three types of analysis to address this question.

First, we estimate a series of 'random effects' models that relate *per capita* GDP in each city to the cluster variables, the level of expenditures *per capita* of all cultural organizations combined, and the level of unemployment in the urban area (as both a measure of underutilized productive capacity as well as the individual economic distress some cities have undergone as a result of industrial restructuring).

The random effects approach is a widely used approach for analysis of panel data. It is particularly recommended when there are unobserved factors that affect the dependent variable (in this case, *per capita* GDP) that are randomly distributed or from which the observations in the panel might be reasonably thought of as a random sample. This permits estimation and (with limitations) statistical inference even in cases where we do not have observations on all variables that are important determinants of local economic prosperity.

Following this analysis, we present a preliminary set of estimates of a panel Vector Auto Regression (VAR) that is arguably even more appropriate to the data situation that confronts us, but is less conclusive. We will see that it indicates a promising direction for further investigation.

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

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
arts expenditures	85.99***	86.20***	87.13***	89.51***	91.28***	95.44***
σ	*14.6*	*14.7*	*14.6*	*14.9*	*14.9*	*15.3*
unemployment	-400.09***	-399.52***	-407.59***	-410.79***	-397.55***	
σ	*35.1*	*35.2*	*35.2*	*35.7*	*35.7*	
median distance	99.69***	100.43***	112.42***	119.90***		
σ	*32.5*	*32.0*	*32.2*	*32.9*		
cluster	1663.35***	1662.13***	1091.25***	1273.88***	1138.25***	1194.74***
σ	*246.3*	*240.7*	*189.1*	*193.9*	*193.6*	*201.6*
maximum gap	-41.55					
σ	*1318.3*					
distance - max gap	19.26***	19.25***				
σ	*5.1*	*5.1*				
signif. peaks	209.57***	209.31***	206.76***			
σ	*37.6*	*37.4*	*37.3*			
constant	27168.40***	27151.01***	27760.01***	27931.96***	28898.79***	26473.68***
σ	*579.2*	*581.4*	*593.1*	*606.7*	*577.0*	*494.2*
σ_u	5066.29	5190.11	5184.15	5216.25	5210.82	5410.41
σ_e	3348.85	3348.70	3359.19	3385.70	3405.18	3461.54
ρ	0.70	0.71	0.70	0.70	0.70	0.71
within	0.26	0.26	0.25	0.24	0.23	0.21
between	0.29	0.29	0.28	0.27	0.28	0.24
overall	0.27	0.27	0.27	0.26	0.26	0.22
Wald $\chi 2$	438.49***	436.56***	394.33***	347.18***	289.83***	90.30***

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

Finally 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). The median value across all urban areas of these ratios provides a test of the causal connection between expenditures by cultural nonprofits and local economic prosperity. These ratios, in aggregate, provide a correct and valid test of the theories of 'creative economies' that have 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.

Table 3 presents the results of estimation of six different random effects models using our panel data. Because the parameter estimates are remarkably stable across alternative specifications, we focus our discussion on the results of Model 1. Here we see that all variables are statistically significant except for the variable measuring the maximum gap between the density of cultural organizations and the density of all nonprofits. The two variables that are unrelated to the spatial structure of cultural nonprofits work as we expect (particularly in light of the causality estimates referred to above). An increase in *per capita* cultural expenditures by $1 is associated with an $86 increase in *per capita* GDP. An increase of one percentage point in the local unemployment rate is associated with a $400 decrease in *per capita* prosperity.

What about the impact of cultural concentration? Here we see some very interesting results that have perhaps surprising implications. Increasing the median distance between cultural organizations is associated with increases in *per capita* GDP. An increase from New York's 4 kilometers to Los Angeles's 20 would, all else equal, be associated with about a $1600 increase in *per capita* GDP. On the other hand, being clustered is important as well. A city whose cultural nonprofits are clustered (as defined in Section 2) has *per capita* GDP that is also about $1600 greater than an identical city whose cultural nonprofits are not clustered.

This result suggests that arranging cultural nonprofits that are concentrated in several dispersed clusters would be associated with the largest positive economic impact. This is further substantiated by noting that the impact of increasing the number of significant peaks is positive and significant. Going from the single peak in New York to the five in Los Angeles would, all else equal, be associated with an increase of more than $800 in *per capita* GDP.

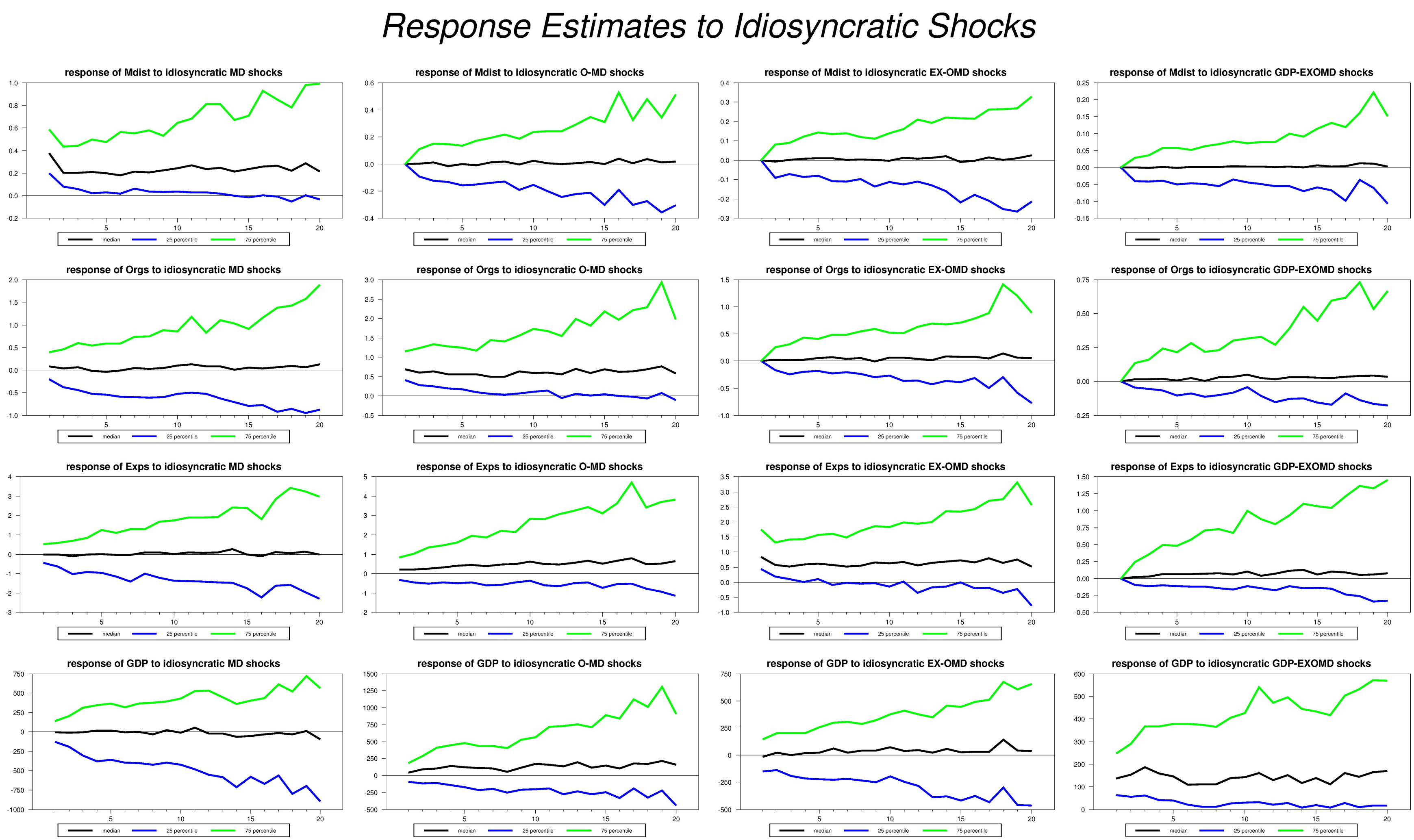

Figure 7: VAR analysis of local per capita GDP: Idiosyncratic shocks

In the models whose estimates are presented in Table 3, we assume that the independent variables - the ones associated with rows in the table - are not correlated with the errors in the dependent variable. There may be unobserved variables that are determinants of local economic prosperity, but the ones that are observed must be independent. For some of the interesting and important variables, this may fail to hold. For example, cultural organizations that are in more affluent urban areas have greater donative resources and hence, as a group, spend more *per capita* than arts nonprofits in less affluent cities.

Panel data such as we have can be analyzed using the techniques of vector auto regression, which allows us to dispense with this assumption and to take into account the interactions and dependencies between the variables. While time and space do not permit a complete analysis along these lines, Figure 7 presents a preliminary analysis that relates *per capita* GDP, median distance between cultural organizations, the number of cultural organizations in a city and the *per capita* expenditures by all cultural organizations.

The panel VAR technique is discussed in detail in Pedroni (2013) and the works cited therein. Essentially, the approach decomposes changes that occur in the system into 'idiosyncratic shocks' that show the impact of a change in one city only, 'common shocks' that affect all cities in the same way, and the 'composite shocks' that are the combination of both of these. Figure 7 shows the response functions to idiosyncratic shocks in a model with *per capita* GDP. The common and composite shock analysis is presented in the Appendix in Figures 9 and 10, respectively.

What these figures reveal is a tremendous variety in responses of urban areas to these shocks. To take one example, consider the results in the graph presented in the lower left-hand corner of Figure 7. This shows the response of *per capita* GDP to a shock in the median distance between organizations. The upper (green) line represents the 75^{th} percentile of urban areas, so a quarter of the cities have a response that is at or above this green line. The lower (blue) line represents the 25^{th} percentile. From the random effects models presented above, we inferred that the average effect to an increase in median distance is positve, but here we see that there is a range of responses - some positive and some negative. This suggests the possibility of using the VAR dynamics established for each city to identify and rank cities by their likely response (based on past observation) to an increase or decrease in cultural concentration. Such results could provide a useful guide to policy, and could potentially figure in the scoring of proposals for allocation of scarce funds available for support of cultural organizations.

Finally, we ask how cultural concentration might affect the inference, presented in Pedroni & Sheppard (2013) that positive shocks to (increases in) *per capita* spending by cultural nonprofits in a city can be causally linked to long run increases in *per capita* GDP. 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 these organizations.

Table 4: Quantile regression analysis of causality ratios

Variable	Model 1	Model 2	Model 3	Model 4
cluster	0.0722 **	0.0760**	0.0416	0.0424
σ	*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**
σ			0.013	0.014
GDP				0.0031
σ				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

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

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.

To put these results in perspective, it is worth remembering that the median speed-of-adjustment ratio for all cities 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.

5 Agglomeration and organizational 'sustainability'

Next we consider how clustering affects the sustainability of cultural nonprofits. Measuring the sustainability of nonprofits is controversial and difficult, and scholars have used a wide range of measures involving program versus donated revenues, growth rates, and levels of net assets relative to expenditures.

For the analysis in this section, we focus on nonprofit surplus: total revenues from all sources less total expenditures. One advantage of this measure is its direct connection to sustainability: if a nonprofit operates for long with negative surplus, it will not be sustainable. Restoring balance for an organization operating with negative surplus can be achieved through many strategies, and the data available don't always permit inference concerning which strategy is being pursued by the organization. In any event, this provides one way of considering and testing the relationship between cultural concentration and (at least one measure of) sustainability. We use total surplus *per capita*, adjusted for inflation, as the dependent variable in the models presented.

Table 5 presents the results of random effects estimation of 5 different models of *per capita* surplus. The precision with which these parameters are estimated is much lower than in the models of *per capita* GDP. In part this is not surprising. The *per capita* surplus variable is much more volatile than *per capita* GDP, and it is more difficult to explain. Again focusing the discussion on Model 1, we note that as expected, an increase in local GDP is associated with an increase in surplus. Increasing *per capita* GDP by \$10000 would be associated with an increase *per capita* surplus of approximately \$2. Since the sample mean surplus is \$7, such an increase would be potentially important.

An increase in median distance between organizations is associated with reduced surplus. While only statistically significant in Model 4, the magnitude of the estimated parameter is stable across model specifications. This is consistent with agglomeration economies between cultural nonprofits. When it is easier for them to collaborate and interact, such economies would suggest that they can operate more efficiently. This efficiency translates into a stronger surplus. A decrease in the median distance between organizations of about 12 kilometers would be associated with a \$1 increase in *per capita* surplus in the urban area.

In this case, the impact of the cluster variable is really minimal, but it is worth drawing attention to the impact of the number of significant peaks, which is also significant in Model 4. Increasing the number of significant peaks from 1 to 5, as in the New York City to Los Angeles comparison, would be associated with an increase in *per capita* surplus of more than \$1.5.

Overall, the results should be interpreted cautiously because the precision of estimation is not high, but it does seem that cultural concentration that diminishes the distance between organizations or generates a larger number of clusters (which is generally associated with a larger number of significant peaks) will improve the sustainability of cultural nonprofits.

Table 5: Random-effects models of arts nonprofit surplus, 1989-2009

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
gdp per capita	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
σ	*0.0001*	*0.0001*	*0.0001*	*0.0001*	*0.0001*
median distance	-0.0833	-0.0788	-0.0788	-0.0889*	-0.0665
σ	*0.0549*	*0.0549*	*0.0549*	*0.0519*	*0.0438*
cluster	0.0700	-0.0066			
σ	*1.2536*	*1.2390*			
maximum gap	-1.7246				
σ	*2.5915*				
distance at max gap	-0.0089	-0.0091	-0.0090		
σ	*0.0144*	*0.0144*	*0.0119*		
signif. peaks	0.3906	0.3858	0.3860*	0.3936*	
σ	*0.2457*	*0.2463*	*0.2285*	*0.2255*	
constant	0.5750	0.5538	0.5785	0.5050	-0.0582
σ	*2.4648*	*2.4726*	*2.2487*	*2.2568*	*2.1031*
σ_u	10.7815	10.8782	10.9646	10.9847	10.9802
σ_e	19.0655	19.0659	19.0655	19.0643	19.0826
ρ	0.2423	0.2456	0.2485	0.2492	0.2487
within	0.0029	0.0028	0.0029	0.0029	0.001
between	0.0667	0.0694	0.0693	0.0669	0.0713
overall	0.02	0.0206	0.0205	0.0199	0.0192
Wald χ^2	34.01***	33.63***	22.48***	20.75***	19.32***

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

Figure 8 presents a set of impulse-response functions estimated from a panel VAR that incorporates the measure of *per capita* surplus used in the random effects models discussed above. As before, these take into account inter-dependencies between the variables, at the cost of greater difficulty of interpretation.

Again we see a wide range of responses of individual cities. Focusing again on the panel of results presented in the lower left-hand corner, we see that while the median response of *per capita* surplus to a shock in median distance is very small (similar to the estimated parameter in the random effects model) the range of responses exhibited by cities in the time period covered by the sample is much larger. The impulse response functions for shocks that are common across all cities as well as the combined effects of both shocks are presented in the Appendix, Figures 11 and 10.

As with the panel VAR that includes *per capita* GDP, this analysis raises the intriguing possibility of further analysis to identify what features of urban areas are associated with strong positive or negative responses to shocks in cultural concentration. Furthermore, it should be possible to order cities according to their exhibited pattern of responses. This could permit consideration of the local spatial structure of cultural nonprofits and the likely consequences of changes in that structure for sustainability for all organizations in the city.

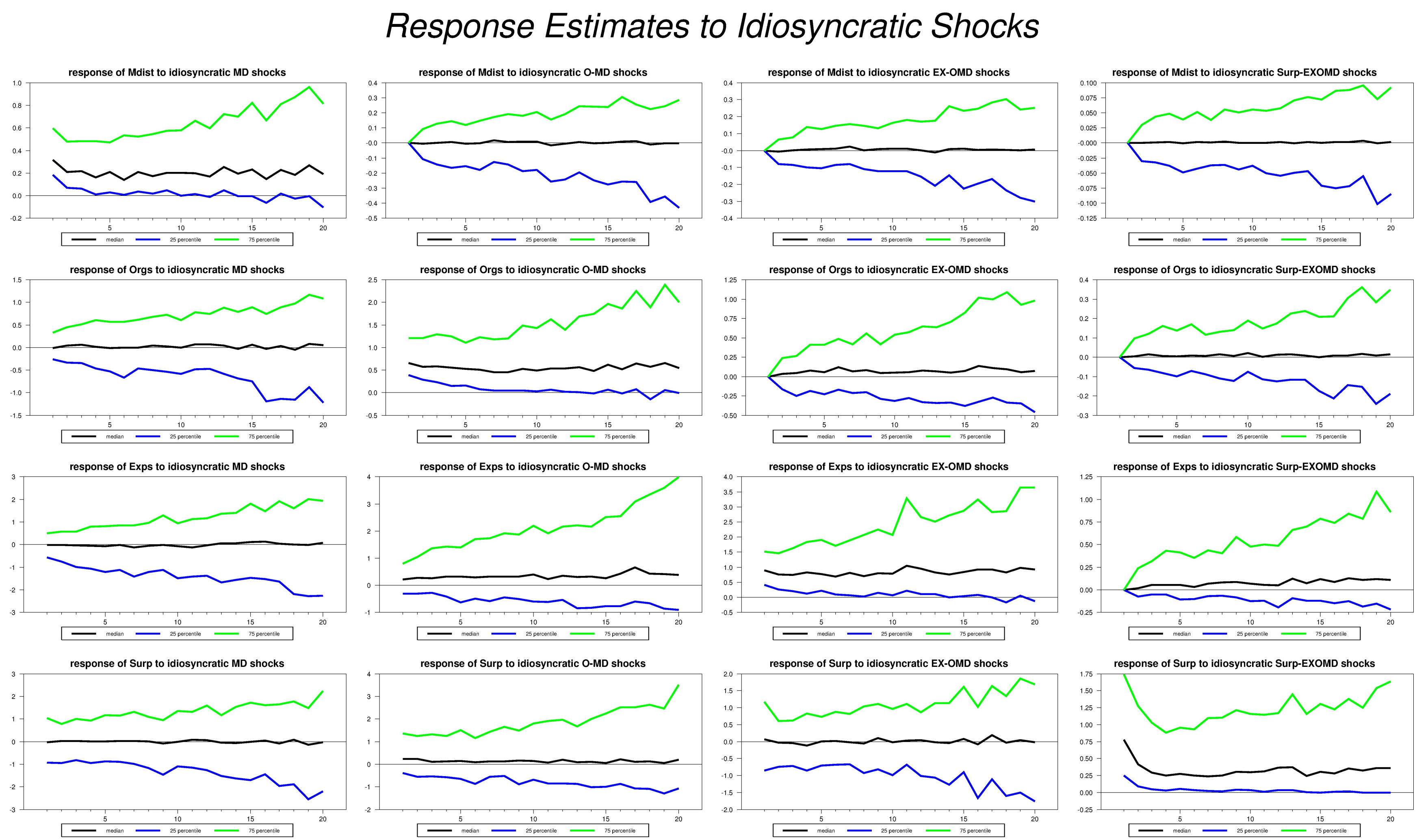

Figure 8: VAR analysis of arts nonprofits surplus per capita: Idiosyncratic shocks

6 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 simple 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 more than 380 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.

The measured impacts on the economic well-being of the organizations themselves are somewhat less clear. The overall result is that increasing the number of separate clusters, and diminishing the median distance between organizations are both associated with increasing *per capita* surplus, and hence economic sustainability, of the organizations in a city. This suggests that there may be a trade-off between efficient operation of cultural non-profits (enhanced by having them be near to one another) and having the maximum impact on the local economy (enhanced by scattering them in clusters around the city and presumably thus making them more accessible to residents). Exploring this trade-off in greater detail should be an important goal of future research.

The paper also presented some preliminary results of estimating panel VAR relationships. These all indicated important heterogeneity in the responses of individual cities *per capita* GDP or surplus to shocks in median distance, numbers of arts organizations and clustering. This suggests the possibility both of further analysis to identify variables that could help identify cities likely to have a positive or negative response to a particular shock, and of ranking or grouping cities based on their observed pattern of responses to such shocks. Further results of this type would again be very helpful for policy makers who are confronted with a very large number of requests for very limited available funds. Research to uncover these relationships could enhance the efficiency of allocation of these scarce funds.

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7 Appendix

Table 6: Descriptive statistics for cluster variables, 2009

Variable	μ	σ	**Min**	**Max**
Median distance	9.31	8.08	0	55
Cluster	0.68	0.47	0	1
Density max gap	0.05	0.10	0.0002	1.0492
Max gap distance	0.05	0.10	0.0002	1.0492
Signif. peaks	2.41	3.55	0	20
# 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 7: Cluster statistics for individual US MSAs, 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
Baton Rouge, LA	10.14	1	0.0072	0.01	3	55	649	117
Battle Creek, MI	26.11	0	0.0005	0.00	0	10	120	53
Bay City, MI	8.20	0	0.0000	0.00	0	9	80	23
Beaumont-Port Arthur, TX	8.78	0	0.0000	0.00	0	26	228	62

Continued on next page

Table 7 – *Continued from previous page*

Urban Area	**Median distance**	**Cluster**	**Density max gap**	**Max gap distance**	**Signif. peaks**	**# Arts orgs**	**# Non-profits**	**MSA 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

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Table 7 – *Continued from previous page*

Urban Area	**Median distance**	**Cluster**	**Density max gap**	**Max gap distance**	**Signif. peaks**	**# Arts orgs**	**# Non-profits**	**MSA 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

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Table 7 – *Continued from previous page*

Urban Area	Median distance	Cluster	Density max gap	Max gap distance	Signif. peaks	# Arts orgs	# Non-profits	MSA 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

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Table 7 – *Continued from previous page*

Urban Area	Median distance	Cluster	Density max gap	Max gap distance	Signif. peaks	# Arts orgs	# Non-profits	MSA 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

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Table 7 – *Continued from previous page*

Urban Area	Median distance	Cluster	Density max gap	Max gap distance	Signif. peaks	# Arts orgs	# Non-profits	MSA 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

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Urban Area	**Median distance**	**Cluster**	**Density max gap**	**Max gap distance**	**Signif. peaks**	**# Arts orgs**	**# Non-profits**	**MSA 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

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Urban Area	Median distance	Cluster	Density max gap	Max gap distance	Signif. peaks	# Arts orgs	# Non-profits	MSA 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

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Urban Area	**Median distance**	**Cluster**	**Density max gap**	**Max gap distance**	**Signif. peaks**	**# Arts orgs**	**# Non-profits**	**MSA 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

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Table 7 – *Continued from previous page*

Urban Area	Median distance	Cluster	Density max gap	Max gap distance	Signif. peaks	# Arts orgs	# Non-profits	MSA 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

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Table 7 – *Continued from previous page*

Urban Area	Median distance	Cluster	Density max gap	Max gap distance	Signif. peaks	# Arts orgs	# Non-profits	MSA 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

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Table 7 – *Continued from previous page*

Urban Area	Median distance	Cluster	Density max gap	Max gap distance	Signif. peaks	# Arts orgs	# Non-profits	MSA 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	61
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	91
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	66
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

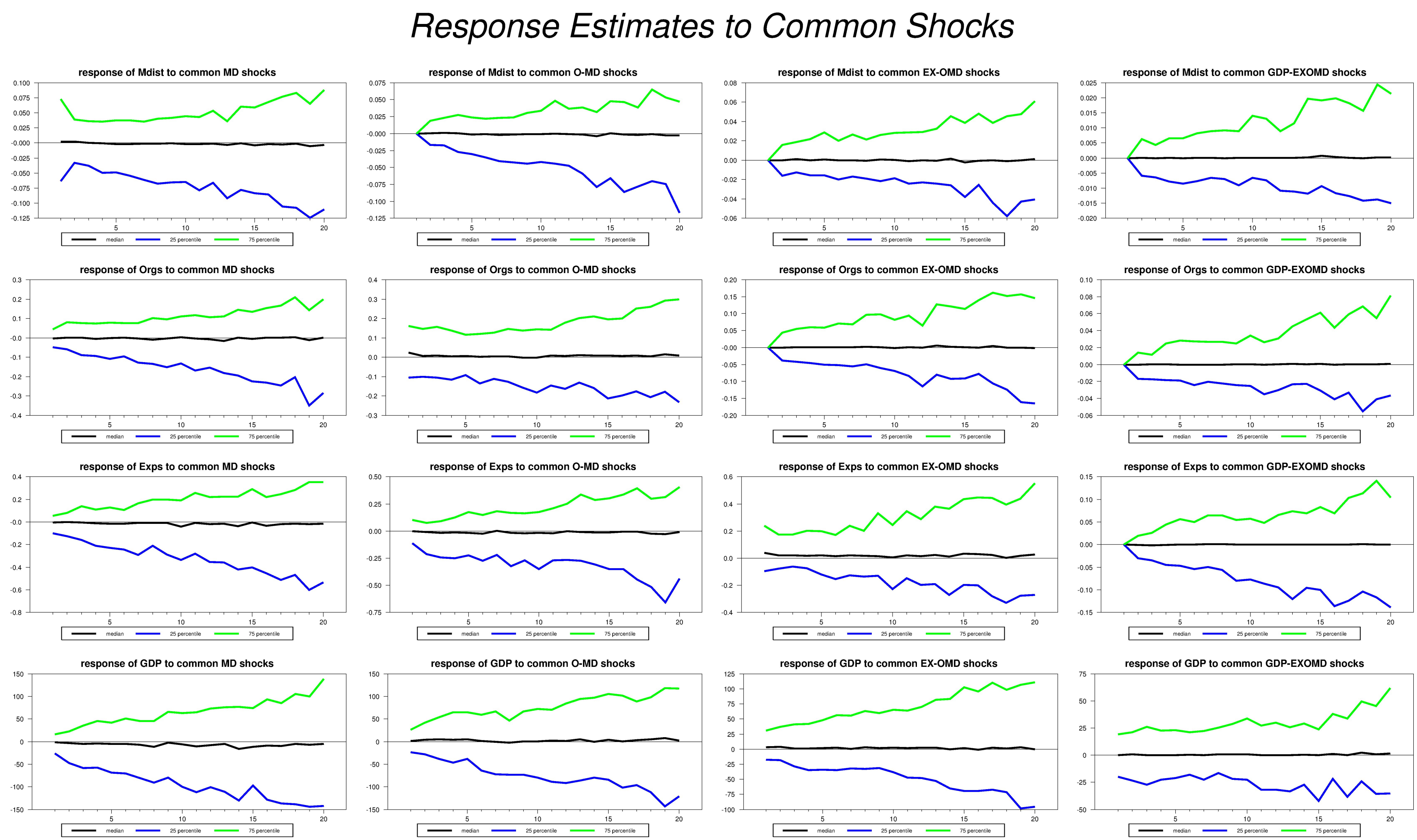

Figure 9: VAR analysis of local per capita GDP: Common shocks

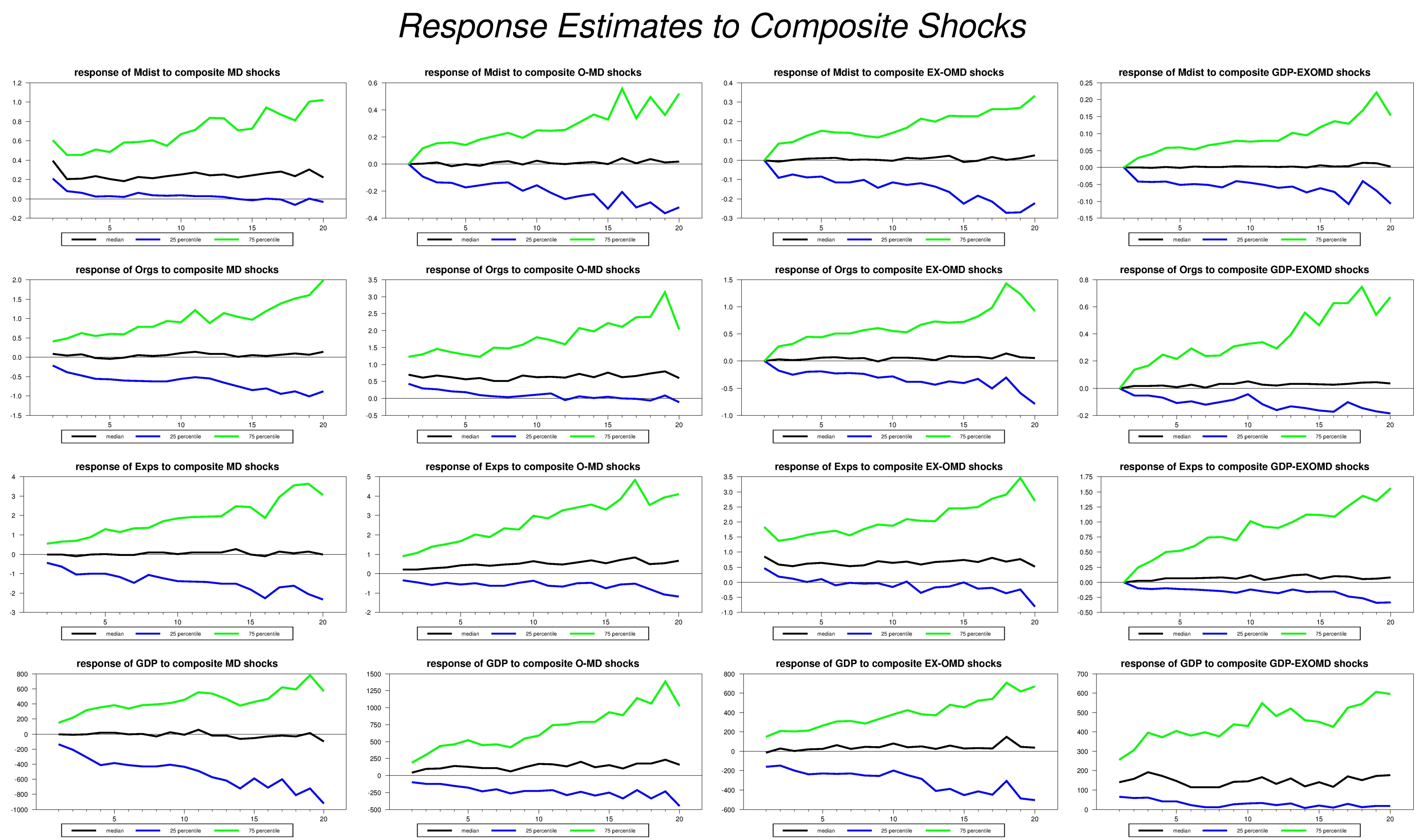

Figure 10: VAR analysis of local per capita GDP: Composite shocks

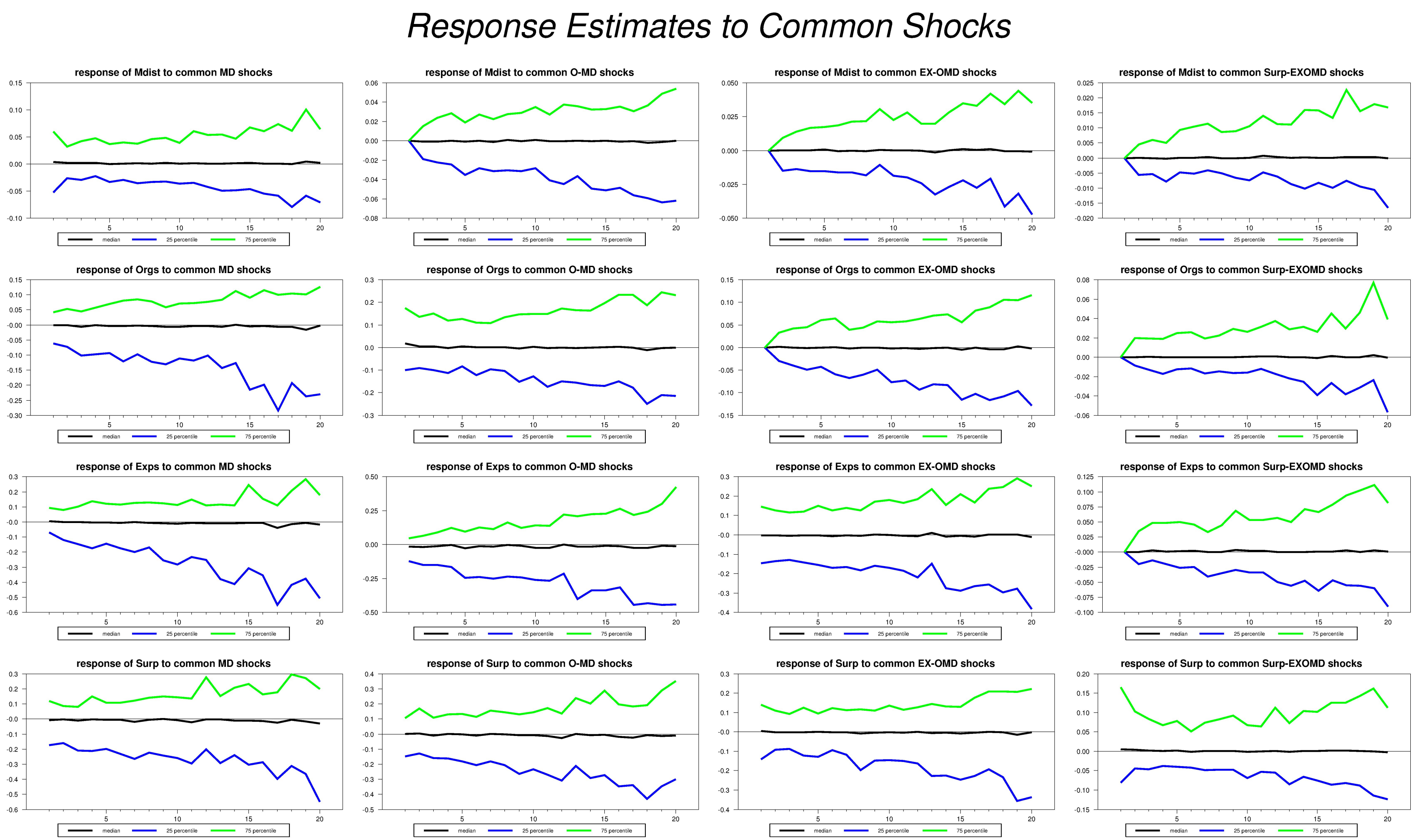

Figure 11: Structural VAR analysis of arts nonprofits surplus: Common shocks

Response Estimates to Composite Shocks

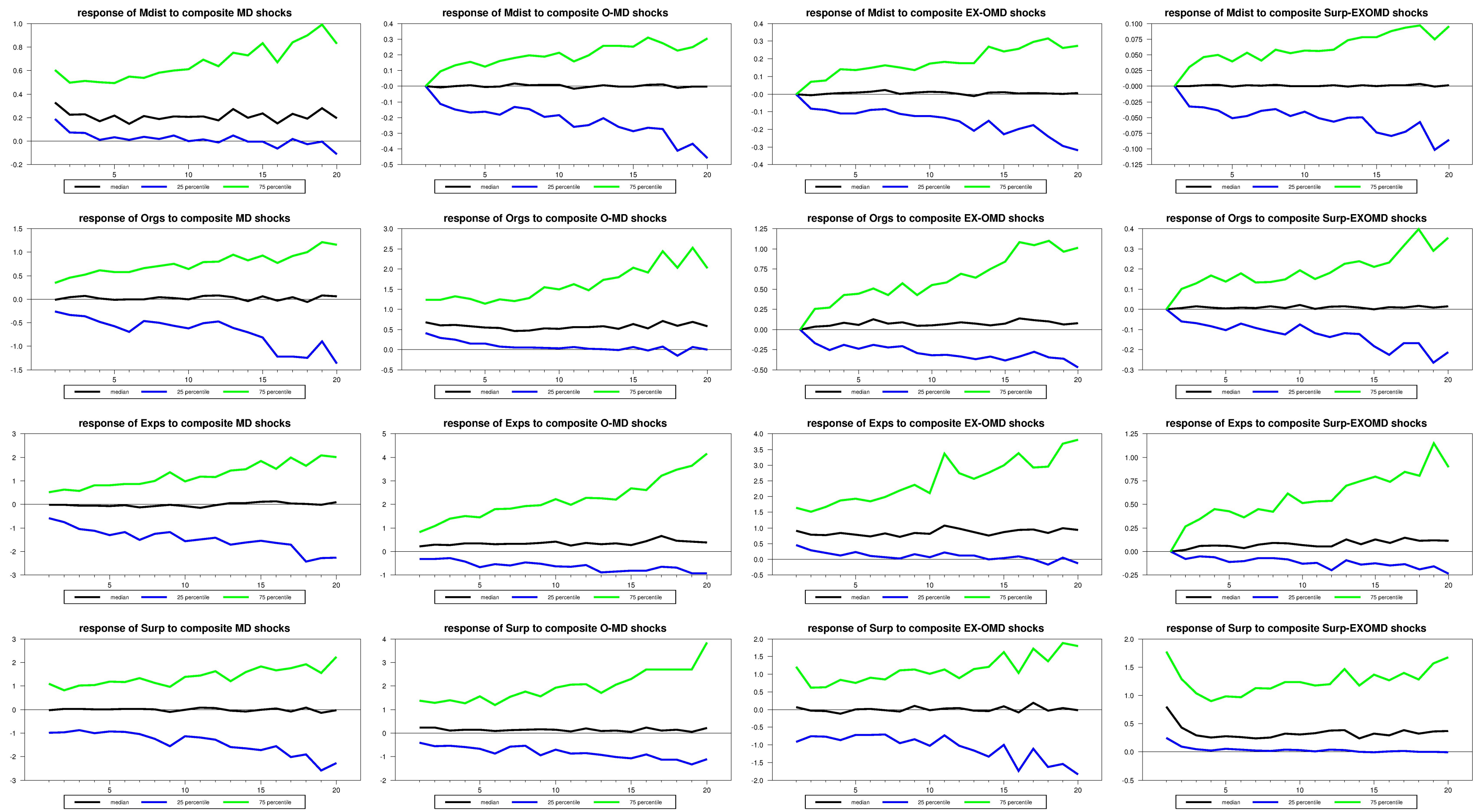

Figure 12: Structural VAR analysis of arts nonprofits surplus: Composite shocks