

# **Constrained pathways to a creative urban economy**

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# Constrained pathways to a creative urban economy

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**Abstract** Creative occupations are now widely seen as a basis for urban economic prosperity. Yet the transitional pathways from a city's current economy to a more creative economy are often difficult to discern or to navigate. Here we use a network perspective of occupational interdependencies to address questions of urban transitions to a creative economy. This perspective allows us to assess alternative pathways and to compare cities with regard to their progress along these pathways. We find that U.S. urban areas follow a general trajectory towards a creative economy that requires them to increasingly specialize, not only in creative occupations, but also in non-creative ones – presumably because certain non-creative occupations complement the tasks performed by related creative occupations. This secondary phenomenon creates a pull towards non-creative occupations that becomes ever stronger as a city moves more towards a creative economy. Thus, cities transitioning to more creative economies experience an overall diversification of specialized occupations, but at a greater rate for creative occupations. Indeed, we find that cities with the most creative economies also have the highest diversity of specialized occupations.

**Keywords:** Networks, occupations, interdependence, urban transitions, economic growth

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## 1. Introduction

Recent scholarship on economic growth has highlighted the importance of knowledge creation and exchange as the main drivers of development through its effects on productivity improvements and technological change (Barro and Sala-i-Martin, 2003; Romer, 1986; Romer, 1990; Lucas, 1988). Arthur (2009) and Romer (2010) both highlight that technologies are ultimately ideas about how to rearrange matter, energy and information to fulfill a human need or purpose. The non-rivalry of ideas, a crucial tenet of the endogenous growth literature, implies that the greater the number of individuals effectively engaged in the creation and sharing of ideas, the greater the production of ideas. Jones and Romer's (2010) review of our current understanding of the sources of economic growth highlights the virtuous cycle between increasing the number of individuals engaged in the generation of ideas and economic growth.

Rather obviously, the principal agents responsible for the generation, recombination and transmission of ideas (that is, knowledge) are individuals. Lucas (1988) explicitly identified the role of human capital – the stock of knowledge and information embodied in individuals – in knowledge creation. The role of individuals as carriers of knowledge is also emphasized by the research highlighting the economic importance of “knowhow” and “routines”: the tacit knowledge, competences, skills and experiences which make it possible to integrate technical knowledge and perform specific tasks (Hausmann and Hidalgo, 2011; Hausmann and Rodrik, 2003; Nelson and Winter, 1982; Dosi et al., 1994). Because individuals are the primary drivers of idea generation and transmission, we focus our study where individuals aggregate: cities.

Much work on urban productivity and urban economic development has also emphasized the importance of human capital (e.g., Abel et al., 2012; Glaeser, 2011; Storper, 2013). Yet despite the enormous explanatory role that human capital is asked to played, and the multi-

dimensional nature of the phenomenon it is expected to represent, the common approach for measuring it, dating from Mincer's (1958) and Becker's (1964) work, is simply educational attainment (usually the share of a population with a bachelor's degree and above). The difficulties of equating human capital with educational attainment, stemming principally from differences in the quality of the education received by individuals and the differences in the economic relevance among types of schooling, have been amply discussed (e.g., Mulligan and Sala-i-Martin, 2000). The importance of face-to-face knowledge transfers and of tacit knowledge as drivers of development has also found an echo in the urban economics and economic geography literature (e.g., Gertler, 2003; Storper and Venables, 2004). And here too educational attainment is an impoverished metric as it cannot adequately capture an individual's accumulated experience, nor their creativity or skills.

Examining human capital alone only tells us demographic characteristics of a population as opposed to the potential value that individuals bring to an urban economy. Educational attributes only measure the available stock, but do not tell us what people do with the education they have acquired. One prominent line of research (Florida, 2012) suggests an alternative, or at the very least, complementary, measure of human capital, based on occupational skills, specifically a set of knowledge-intensive occupations that make up the "creative occupations." A crucial difference between educational attainment and occupation-based measurements of human capital is that educational attainment is a measure of the supply of talent, while creative employment measures the demand for it: in order for an individual to perform a "creative" occupation, someone needs to be willing to pay for the person's talent. Florida (2012) separates education from creativity, defining education as what you have studied for and creativity as what you do in practice. This does not replace education-based measures of human capital in studies

of regional and urban economic development, but should be seen as a complementary measure (Florida et al., 2008; Lobo et al., 2014).

An important feature of occupations, essential to the existence of a division of labor, is that they need to be performed jointly to create wealth. Modern economies are intricate webs linking specialized production units (Acemoglu et al., 2012; Atalay et al., 2011; Fujiwara and Aoyama, 2010; Hidalgo and Hausmann, 2009). What goods and services such units can provide, and how well they provide them, is largely determined by the technologies, skills, and tacit knowledge integrated in the process of value creation. It is the *interconnections* among these technologies and skills form an economic structure, enabling some developmental pathways while foreclosing others. The ease with which an economy can navigate this structure and shift to new activities is largely determined by its current portfolio of technologies and skills (Grossman and Helpman, 1993; Lucas, 1993; Rosenberg, 1983; Stokey, 1988; Stokey, 1991). Recent work (Hausmann and Hidalgo, 2011; Hidalgo and Hausmann, 2009; Hidalgo et al., 2007) shows that such a structure is indeed crucial for understanding the economic development at the national level: the technologies and skills prevalent in the economy of a country, embodied in the goods it produces and services it provides, place that economy in a specific region of a global “product space” and constrain the ease with which that national economy can transform its production structure.

Building on this understanding of economic structure we recently developed an explicitly structural perspective to explore urban occupational transformations, resulting in the construction of an occupational space applicable to all U.S. metropolitan economies (Muneepeerakul et al., 2013). In that work we used the term “space” metaphorically, and our creation is more accurately defined as a network of interdependent occupations. The construction of this network

relies on occupational data, which capture the skills and human capital characteristic of a particular city's economy (Florida, 2012; Florida et al., 2008; Gabe et al., 2012; Glaeser, 2011; Jones and Romer, 2010; Moretti, 2012). These occupations are defined by the U.S. Bureau of Labor Statistics (BLS), based on the work carried out and on the skills, education, training, and credentials needed to perform the specified work tasks. Thus, occupational data capture not only the products and services, but also the skills that characterize urban economies (Gabe et al., 2012; Moretti, 2012).

To better understand how different occupations contribute to urban development, we use a classification developed by the U.S. Department of Agriculture that designates certain occupations as *creative* occupations (USDA, 2015). Using this classification, along with employment data from the BLS and the analytical framework of an *occupation network*, we investigate the nature and strength of the interrelationships both among creative occupations and between creative and non-creative occupations. Through these interrelationships we explore the extent to which the dominant skills currently present in a city constrain the city's ability to transform into a creative economy.

## **2. Data and Methods**

### **2.1. Data**

Our spatial units of analysis are the 364 Metropolitan Statistical Areas (MSAs) of the United States. MSAs consist of a core county, or counties, in which a city having a population of at least 50,000 is located, plus adjacent counties having a high degree of social and economic integration with the core counties as measured through commuting ties. MSAs are in effect unified labor markets and encompass geographical areas of high economic cohesion. Together the nation's metropolitan areas account for nearly 85% of U.S. population and over 90% of U.S.

economic output (see US Census Bureau, 2015: for a discussion of how MSAs are defined). When we use the terms “city” or “urban areas” herein, we are referring to MSAs.

We utilize three data sets: (a) Occupational data tabulating how many workers were employed annually in each different occupation in each U.S. city, (b) relevant economic indicators for each U.S. city, and (c) a classification of occupations as creative or non-creative. The first set was obtained from the Bureau of Labor Statistics’ (BLS) Occupational Employment Survey (OES) datasets. These data include the estimated number of people employed in each of approximately 800 occupations for each metropolitan statistical area (MSA) of the U.S. These numbers are estimated annually by the BLS. In this study we use data from 2005 to 2013.

Economic measures and population demographics were obtained from the U.S. Census Bureau and include, for each metropolitan statistical area in the U.S., annual estimates of real per capita GDP, real per capita personal income, population size, and population-weighted density. Regarding which occupations are designated as creative or non-creative, we adopt the classification scheme developed by the Economic Research Service (ERS), an agency of the U.S. Department of Agriculture (USDA, 2015). This allows us to classify all occupations tracked by the BLS as either creative or non-creative occupations. Because the ERS classifications are subject to periodic changes and because other researchers may wish to define their own classification of creative occupations, our methodology is generalized enough to accommodate these alternative definitions.

## 2.2. Occupational Interdependence Network

To study how cities can transition toward more creative economies, we build a network that quantitatively captures the interdependencies between various labor occupations. In this network, nodes are occupations and the weight of the link between any two nodes is the degree

to which those two occupations are interdependent upon one another. This network enables us to address the notion of proximity between different occupations, between the occupational structure of different cities, and between different sets of occupations.

In defining an urban economic structure we focus on those occupations in which a city specializes. An MSA is considered to be specialized in an occupation if the proportion of the city's labor force engaged in that occupation is greater than the same proportion nationally. Thus, specialization can be stated in terms of the widely used location quotient, which for occupation  $i$  in MSA  $m$  is defined as:

$$LQ_i^{(m)} = \frac{(x_i^{(m)} / \sum_i x_i^{(m)})}{(\sum_m x_i^{(m)} / \sum_m \sum_i x_i^{(m)})} \quad 1)$$

where  $x_i^{(m)}$  is the number of workers employed in occupation  $i$  in MSA  $m$ . MSA  $m$  is specialized in occupation  $i$  if its location quotient  $LQ_i^{(m)} > 1$ . We take this specialization as a proxy for the aggregate comparative advantage that a given urban economy has for that occupation. The set of all such specializations within a given city, which we term the *set of occupational specializations* (SOS), is used to define the city's current economic state. The SOS of a city is represented by the set of nodes the city occupies in the occupational interdependence network.

Next we calculate a measure of interdependence between every pair of occupations, which are weights of the links in our occupational network. This measure must capture the fact that a pair of occupations may be positively *or* negatively linked. Positively linked occupations tend to occur together in the same city. They may jointly contribute to the production of a common economic output or may otherwise rely on one another. Surgeons and anesthesiologists

are two such occupations that are positively linked. On the other hand, occupations might interact negatively if they compete for common skills, as is the case with retail salespersons and door-to-door salespersons. Having defined each city's set of occupational specializations (SOS), we then use the co-location patterns of those occupations among all cities to define the interdependence between any two occupations  $i$  and  $j$ ,  $\zeta_{ij}$ , as:

$$\zeta_{ij} = \frac{P[LQ_i^{(m)} > 1, LQ_j^{(m)} > 1]}{P[LQ_i^{(m')} > 1] P[LQ_j^{(m'')} > 1]} - 1 \quad 2)$$

where  $m$ ,  $m'$ , and  $m''$  denote a randomly selected MSA (Muneepeerakul et al., 2013). Thus, our measure meets our criteria of being positive when two occupations co-occur in a city more frequently than expected by chance, and of being negative when they co-occur less frequently.

Finally, we use these interdependencies to build the *occupational interdependence network*. A visual representation of this network, based on 2013 data, is shown in Fig. 1A (links have been removed for visual clarity). Note that occupations are not uniformly distributed across this figure. The network contains a dense core of highly interdependent occupations and a periphery of occupations that tend to be weakly or negatively interdependent with others. In Fig. 1A, occupations  $i$  and  $j$  tend to be, on average, close to each other if  $\zeta_{ij}$  is positive and farther apart if  $\zeta_{ij}$  is negative.

### 2.3. The Creative Jobs Index

We may now pose the question, “what is the similarity or proximity between a city's current economy and the ultimate creative economy?” A maximally creative urban economy is one in which a city specializes in all occupations classified as creative. The nodes comprising this

ultimate creative economy within the occupational network is shown in Fig. 1B. Note that these creative occupations are concentrated in the highly interdependent core, with only a few positioned at the periphery. This figure reveals that the occupations closest to a given creative occupation – i.e., those having the greatest positive  $\zeta$ 's with the given creative occupation – need not themselves be creative. The same is true for non-creative occupations, their nearest neighbors may be creative occupations. Intuitively, Fig. 1 already suggests that transition to the creative economy will not be straightforward and that the notion of proximity between economic states within this network is difficult to visually grasp and therefore needs proper quantification.

The difficulty or ease of specializing in the next occupations on a city's path toward the creative economy is largely determined by the city's current SOS. The creative occupations in which a city is most likely to specialize next are tightly surrounded by the city's current specialties, e.g., the yellow nodes surrounded by the orange and/or gray nodes in Figs. 1C and 1D. While we show visually that these nodes are in close proximity, on average, to a city's current SOS in the network, our ultimate goal is to rigorously quantify this proximity.

For each occupation  $i$  in which a city does *not* currently specialize, we develop a measure of proximity between  $i$  and the city's current economic state. We term this measure the unspecialized occupation's transition potential  $V_i$ . Given the interdependencies  $\zeta$  between occupation  $i$  and all occupations currently specialized in a city (SOS) we define the transition potential of  $i$  as:

$$V_i(\text{SOS}) = 1 - \prod_{j \in \text{SOS}} (1 - c(\zeta_{ij} + 1)P[LQ_i > 1]) \quad (3)$$

where  $c$  is simply a tuning parameter chosen to result in a useful range of values of  $V$ . Thus, the transition potential of occupation  $i$  is essentially a measure of the relative ease with which an MSA may become specialized in occupation  $i$  in the future.

Calculating this transition potential for all creative occupations and aggregating into a single metric, we create what we term here the Creative Jobs Index. More precisely, the Creative Jobs Index of an MSA  $m$ ,  $C^{(m)}$ , is defined as:

$$C^{(m)} = \frac{1}{N_C} \sum_{i \in \text{SOS}_C} V_i(\text{SOS}_0^{(m)})^{1-\delta_i} \quad (4)$$

where  $\text{SOS}_C$  denotes the SOS of the ideal creative economy (Fig. 1B),  $\text{SOS}_0^{(m)}$  the current SOS of MSA  $m$ , and  $N_C$  the total number of creative occupations so designated by the ERS.  $\delta_i$  is an indicator function: it is 1 if MSA  $m$  already specializes in occupation  $c$  and 0 otherwise. Thus, a creative occupation  $c$  has the value of 1 if the MSA already specializes in that occupation and has the value of  $V_c$  if it does not. In the event that city  $m$  already specializes in all  $N_C$  creative occupations, its Creative Jobs Index  $C^{(m)} = 1$ .

Note that  $C^{(m)}$  can be decomposed into two, more intuitive, terms as follows:

$$\begin{aligned} C^{(m)} &= \left( \frac{1}{N_C} \sum_{i \in \text{SOS}_C, \delta_i=1} 1 \right) + \left( \frac{1}{N_C} \sum_{i \in \text{SOS}_C, \delta_i=0} V_i(\text{SOS}_0^{(m)}) \right) \\ &= C_{now}^{(m)} + C_{rem}^{(m)} \end{aligned} \quad (5)$$

The first term,  $C_{now}^{(m)}$ , is simply the fraction of all creative occupations in which the city is already specialized, thereby representing how creative the city is *now*. The second term,  $C_{rem}^{(m)}$ , measures the ease with which the city would specialize in the *remaining* creative occupations – those in

which the city has not yet specialized. It is important to recognize that this ease critically depends on what occupations—both creative and non-creative—the city is already specialized in and their interdependence with the remaining creative occupations. In a sense,  $C_{rem}^{(m)}$  captures (with apologies to our physicist friends) the “momentum” of past transitions that are carrying the city further toward the creative economy.

#### 2.4. The Non-creative Jobs Index

Due to the intertwined complexity of the occupation network—with its positive and negative weighted links—considering only the creative economy offers a rather incomplete picture. In this network, a single occupation is linked simultaneously to many creative and non-creative occupations. As a result, by specializing in one additional occupation, a city may move closer to *both* the creative and non-creative economies. To capture the complete picture of the transition toward the creative economy, we similarly define, and decompose, the Non-creative Jobs Index  $X^{(m)}$  as follows:

$$\begin{aligned}
 X^{(m)} &= \left( \frac{1}{N_X} \sum_{i \in \text{SOS}_X, \delta_i=1} 1 \right) + \left( \frac{1}{N_X} \sum_{i \in \text{SOS}_X, \delta_i=0} V_i(\text{SOS}_0^{(m)}) \right) \\
 &= X_{now}^{(m)} + X_{rem}^{(m)}
 \end{aligned} \tag{6}$$

where  $\text{SOS}_X$  denotes the SOS of the non-creative economy (the set of all occupations that are not creative) and  $N_X$  the total number of non-creative occupations. The two terms can also be similarly interpreted to those comprising  $C^{(m)}$ :  $X_{now}^{(m)}$  is the fraction of all non-creative occupations in which the city is already specialized;  $X_{rem}^{(m)}$  measures the ease with which the city would specialize in the *remaining* non-creative occupations – those in which the city does not yet

specialize. Considering  $C_{now}^{(m)}$ ,  $C_{rem}^{(m)}$ ,  $X_{now}^{(m)}$ , and  $X_{rem}^{(m)}$  together provides a comprehensive picture of where a city  $m$  currently is in this creative-non-creative spectrum and in which direction its economy is being pushed by its momenta, namely,  $C_{rem}^{(m)}$  and  $X_{rem}^{(m)}$ .

### 3. Results

Based on the 2013 data of the 364 MSAs, Table 1 lists the 10 MSAs closest to the creative economy (highest values of  $C$ ) and the 10 MSAs furthest from the creative economy (lowest values of  $C$ ). The positions of cities in this ranking are relatively stable over time, with Boston, San Francisco, and Washington, DC occupying the top three positions in all years of our study, though the order of the three varied. For demonstration purposes, SOSs of two cities – one highly creative and the other much less creative – are shown in relation to the full occupational network in Figs. 1C and 1D.

[Figure 1 about here]

[Table 1 about here]

We now examine the benefits associated with having a more creative urban economy, as alluded to in our introduction, by considering the relationship between  $C$  and measures of economic performance: population, weighted population density, real per capita GDP, and real per capita personal income. Results shown in Fig. 2 display such a positive relationship in all cases, though we make no inference regarding causality.

[Figure 2 about here]

To better understand the “tension” between the movement towards creative jobs and the pull towards non-creative jobs, we compare  $C^{(m)}$  and  $X^{(m)}$  of all 364 MSAs in our study (Fig. 3). The relative magnitudes of these two indices capture how a city is pulled between two ends of the creative economic spectrum. We identify three categories of urban economies that emerge

based on a city's creative and non-creative job indices: those that are always (during the period of our analysis, 2005-2013) closer to the non-creative economy, those that are always closer to the creative economy, and those that fluctuate with regard to which economic state is closer. We term these three categories non-creative economies, creative economies, and transitional economies, respectively. Mean quantitative attributes of the cities comprising these three categories are presented in Table 2.

[Figure 3 about here]

[Table 2 about here]

#### 4. Discussion

Table 2 shows that, while a large majority of U.S. cities ( $N = 307$ ) is always closer to the non-creative economy, a small group of large cities ( $N = 19$ ) has managed to continuously stay in the creative category. This small group appears superior in its ability to attract workers with creative skills, while experiencing stronger economic performance in several measures. Furthermore, the gap between creative economies and non-creative economies is growing, as mean annual increases in  $C$  among creative economies is three times higher than that among non-creative economies in what might be considered a case of increasing returns.

Figure 3 reveals that, in general, as cities move closer to the creative economy, they also move closer to the non-creative economy. How can this be? Recall that our proximity measures are defined by the network of occupational interdependences – an intricate web of both creative and non-creative occupations. For a city to move toward either economic state, it must become increasingly specialized in occupations associated with one of the states, which, in a network, a city may do simultaneously for both types of jobs. Thus, as cities become more creative, they also specialize in a wider range of occupations (including non-creative ones) (Figure 4).

[Figure 4 about here]

Put another way, Figure 4 suggests that cities with low creativity specialize in only a few jobs, while those with high creativity specialize in many. Again, because occupational specialties are determined by  $LQ$ , employment in those cities with low numbers of specialty occupations must be dominated those few specialties. Thus, empirically we find an argument for occupational diversity and its contribution to creativity and economic performance. One possible explanation is that when a city's labor force and associated skills are concentrated in a small number of occupations, it stifles the competition that drives creativity and leads to a less creative economy.

Another likely manifestation of this growing diversity is that cities in all economic categories are, on average, increasing annually in both  $C$  and  $X$ . As cities grow and become less dependent on a small number of occupations, employees move into new roles, leading to new specializations for the growing city. Those specialization may be either creative or non-creative. Note that annual increases in  $C$  are higher than those in  $X$ , for all types of cities. Yet, because this increase in  $C$  is nowhere accompanied by a decrease in  $X$ , it suggests the possibility that there exists a net flux of creative workers from rural to urban areas (McGranahan and Wojan, 2007), from other countries to the U.S., or a combination of both.

Above we show that as a city moves through the occupational interdependence network, it grows closer to both the non-creative and creative economies. However, this dual progression is not symmetrical. At any given time a city is pulled differentially by the momenta  $C_{rem}$  and  $X_{rem}$ , due to the transition pathway it has taken. A useful method of visualizing this tension is through a vector field as shown in Figure 5. Here, each city is represented as a vector in the  $C$ — $X$  plane. Each vector's origin represents a city's current SOS relative to both the creative and non-creative economies (i.e,  $C$  and  $X$ ), while the vector itself is the composition of  $C_{rem}$  and  $X_{rem}$ .

Thus, a city whose vector has a slope  $> 1$  is being pulled more strongly towards the non-creative economy, while the opposite is true for cities whose vectors have a slope  $< 1$ .

In Figure 6, we compare each city's position relative to the two economic states to the slope of their combined momenta. Here, the city's relative position is represented by its distance to the  $X = C$  line that divides the two economies. The resulting representation in Figure 6 is quite revealing ( $R^2 = 0.82$ ). The further a city strays away from the  $X = C$  line and towards the creative economy, the more strongly its momenta pull the city back towards the non-creative economy. The opposite is true, though not to the same magnitude – as cities drift closer to the non-creative economy, its momenta eventually begin to pull more strongly to the creative economy.

[Figure 5 about here]

However, the equilibrium of this phenomena is not at the boundary between creative and non-creative (the line  $X = C$ ). Instead, all momenta tend to pull economies toward a parallel line above  $X = C$ , in the region closer to the non-creative economy (the dashed line in Figure 5). Thus, there is not only an ever present pull backwards as cities get too close to the creative economy, but this pull is to the non-creative region. One possible explanation for this trend is that, regardless of how many creative occupations are specialized by a city, there is always a need for the specializations of a sufficient number of non-creative occupations that support those creative ones.

[Figure 6 about here]

Taken together, these findings suggest that cities are constrained in their ability to penetrate the creative economy for two reasons. First, to further penetrate the creative economy they must simultaneously penetrate the non-creative economy. This is likely because, for

creative occupations to be present, there are closely interdependent non-creative occupations that must also be present. Thus, any labor force must have a pool of non-creative skills that support and contribute to the growth of creative occupations. Second, the ever present momenta pulling cities away from the creative economy become stronger as a city becomes more creative. To overcome this pull, and to stay closer to the creative economy, a city must continuously attract a net influx of workers with creative skills – an outcome that is only realized by the most competitive cities.

## **5. Conclusions**

Ever since Adam Smith—with his celebrated emphasis on the role of the division of labor—economists have known that the structure of an economy, that is, what it does, and how and by whom, greatly matters for economic development. Recently economists have taken to highlight how the know-how (the ability to perform specific tasks) embedded in an economy’s activities and occupations constrains which developmental paths are actually open. This is the case for urban economies as well. The development of urban areas into “knowledge-intensive” or “creative” economies, by now a widely advocated policy objective, involves structural transformation. How does an urban area’s current set of skills and know-how facilitate or hinder such a transformation?

In this paper, we apply a network perspective to interdependence among occupational specializations in U.S. cities to address urban transitions to a creative economy. The key feature of this perspective is that, what a city is currently specialized in influences the ease or difficulty of its further transitions. Our results show that these cities follow a general trajectory towards a creative economy. As they grow in their occupational diversity, these cities simultaneously—but not uniformly—specialize in both creative and non-creative occupations. Initially, cities tend to

specialize in non-creative occupations, but as they become progressively more diverse, they specialize differentially more in creative occupations. Importantly, as a city approaches the creative economy, the relative ease for it to approach the non-creative economy increases as well. Our results also suggest that while transitioning to a creative urban economy is an aspiration for many cities, maintaining specializations in a significant number of non-creative occupations is a necessary and integral part of that transition.

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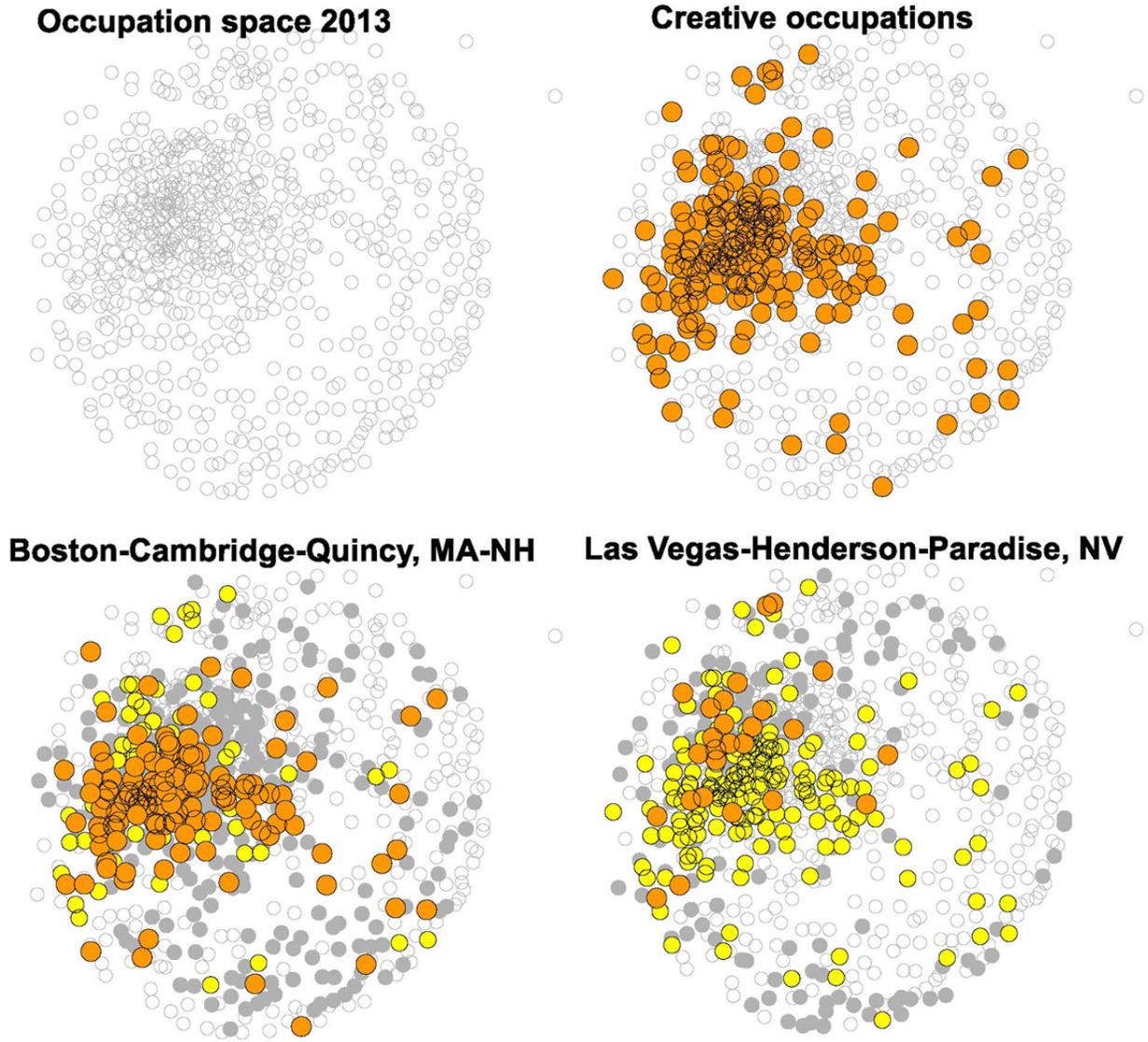
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**Table 1.** The 10 highest and 10 lowest values of Creative Jobs index  $C$  among 364 US metropolitan statistical areas in 2013.

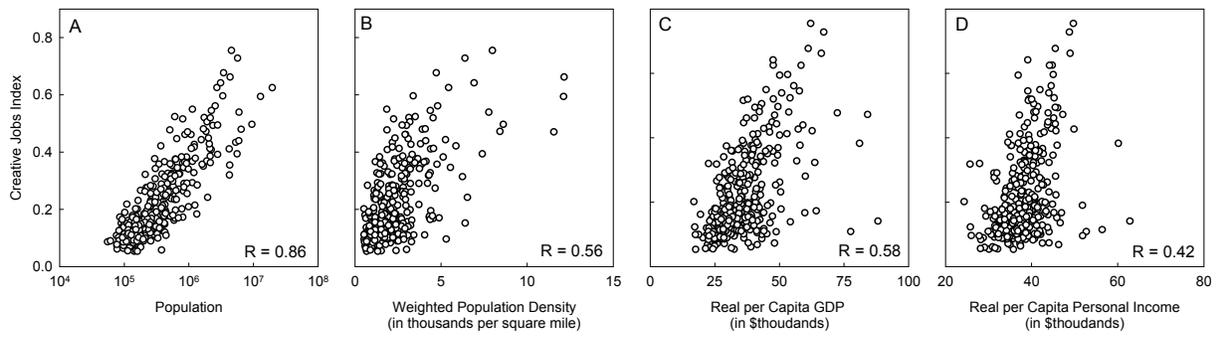
Rank	Metropolitan Statistical Area (MSA)	$C$
1.	Boston-Cambridge-Newton, MA-NH	0.723
2.	Washington-Arlington-Alexandria, DC-VA-MD-WV	0.715
3.	San Francisco-Oakland-Hayward, CA	0.674
4.	Seattle-Tacoma-Bellevue, WA	0.636
5.	Portland-Vancouver-Hillsboro, OR-WA	0.630
6.	Los Angeles-Long Beach-Anaheim, CA	0.630
7.	Minneapolis-St. Paul-Bloomington, MN-WI	0.604
8.	San Diego-Carlsbad, CA	0.602
9.	Denver-Aurora-Lakewood, CO	0.599
10.	Baltimore-Columbia-Towson, MD	0.594
355.	Rome, GA	0.076
356.	Madera, CA	0.073
357.	Bay City, MI	0.071
358.	San Angelo, TX	0.071
359.	Goldsboro, NC	0.065
360.	Burlington, NC	0.063
361.	Punta Gorda, FL	0.062
362.	Hinesville, GA	0.058
363.	Hanford-Corcoran, CA	0.058
364.	Gadsden, AL	0.049

**Table 2. Mean indicator values (2005-2013) for cities of each creative class shown in Fig. 3.**

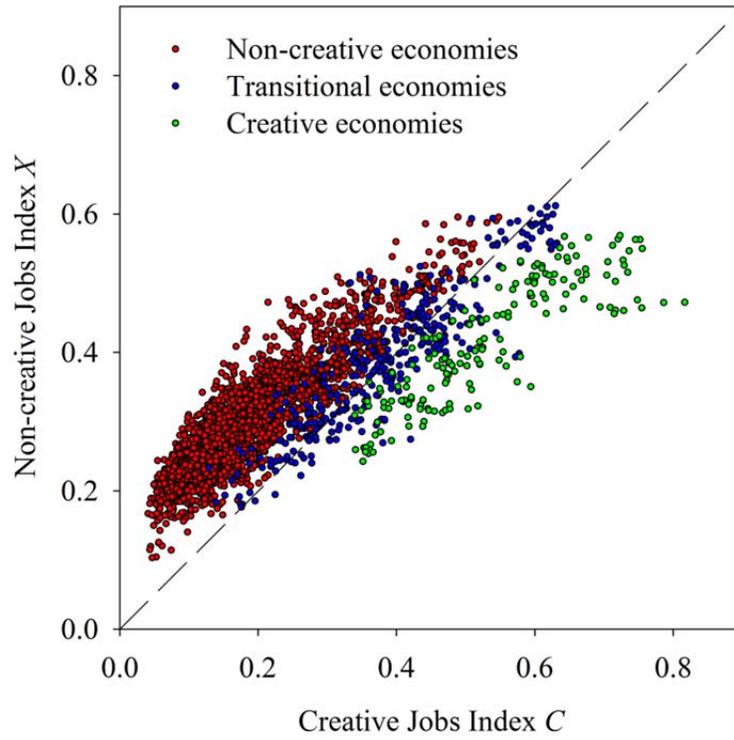
Group	Non-creative	Transitional	Creative	All Cities
Number of cities	307	38	19	364
Population (millions)	0.5	1.9	2.1	0.7
Weighted population density ( $10^3/\text{mile}^2$ )	2.0	4.6	4.7	2.4
Unemployment Rate	7.1	6.2	6.2	7.0
per capita nominal income (\$)	35,160	40,180	46,676	36,285
per capita GDP (\$)	33,223	43,065	59,385	36,581
GDP / Income	0.98	1.08	1.18	1.01
Creative Jobs Index $C$	0.18	0.38	0.53	0.22
Annual change in $C$	0.001	0.004	0.004	0.0017
Annual % change in $C$	0.7%	1.2%	0.7%	0.8%
Non-creative Jobs Index $X$	0.29	0.39	0.42	0.31
Annual change in $X$	0.001	0.000	0.001	0.0008
Annual % change in $X$	0.3%	0.1%	0.3%	0.3%



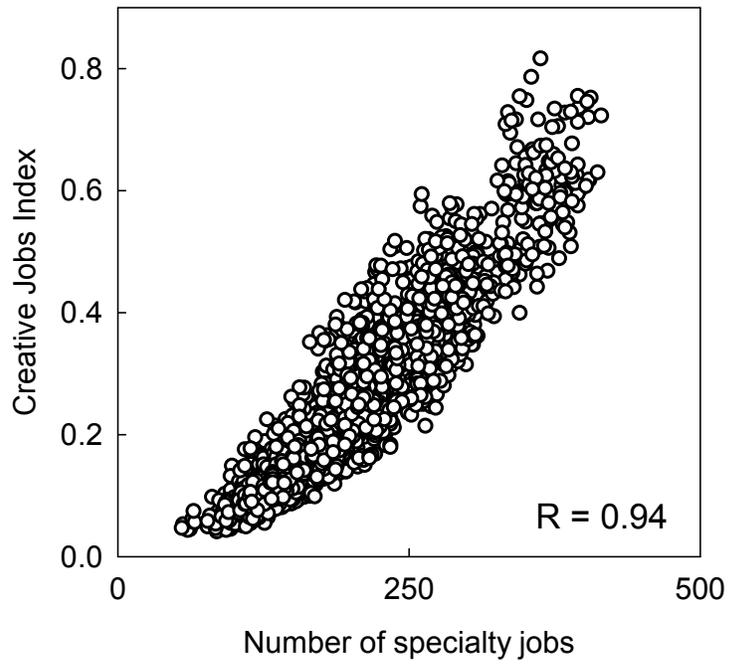
**Figure 1.** The occupational interdependence network and the creative economy therein (based on 2013 data, links removed for clarity): (A) the full network of all occupations recognized by the U.S. Bureau of Labor Statistics; (B) creative occupations as defined by the US Department of Agriculture; (C) specializations for Boston ( $C = 0.723$ , ranked 1<sup>st</sup>); and (D) specializations for Las Vegas ( $C = 0.203$ , ranked 248<sup>th</sup>). In (B) orange nodes represent the creative occupations. Each node represents one occupation and its proximity to other nodes is determined by the interdependence between the nodes' corresponding occupations. In (C) and (D) orange nodes are creative occupations that are current specialties of the MSA; gray nodes are current non-creative specialties; and yellow nodes are creative occupations that are not yet specialties. Positioning of nodes is determined by a non-metric multidimensional scaling algorithm, the aim of which is to match the *ranking* of the pairwise proximity between two nodes  $i$  and  $j$  and the ranking of  $\zeta_{ij}$  as much as possible (closer proximity for larger  $\zeta$ 's).



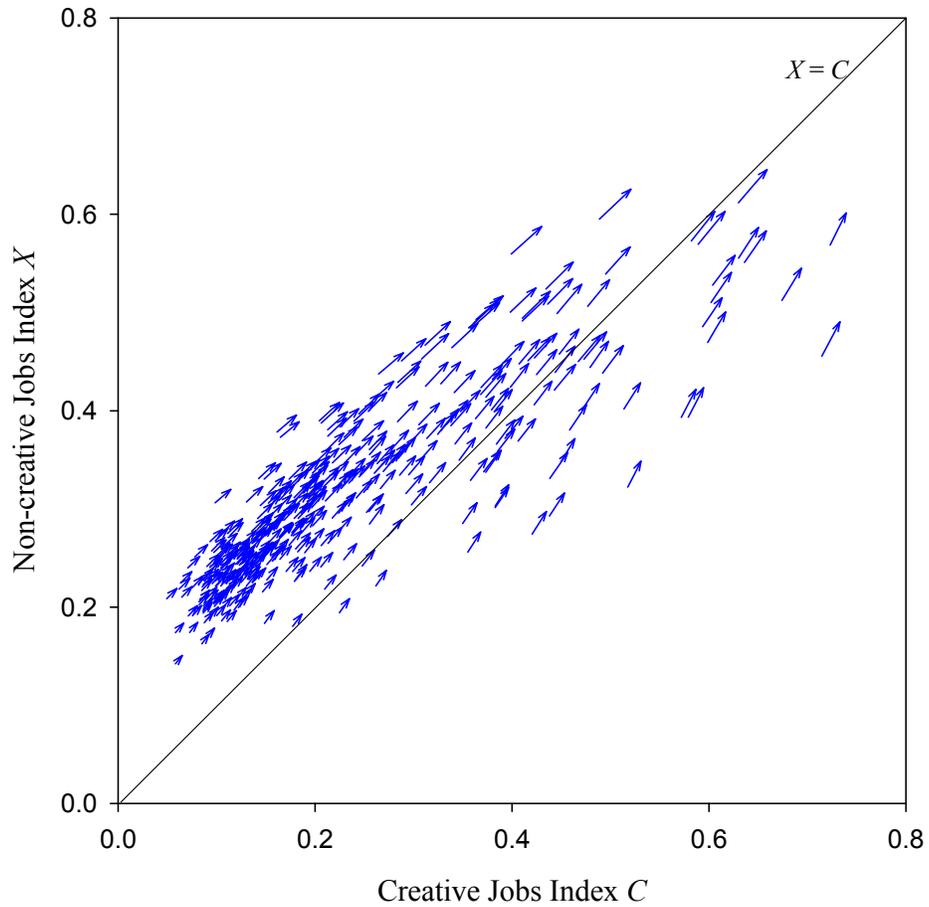
**Figure 2. Creative Jobs Index  $C$  vs. metrics of economic performance.** Data shown are for 2010. Economic performance measures include: (A) population, (B) weighted population density, (C) real per capita GDP, and (D) real per capita personal income. Note that the population axis in panel (A) is logarithmic.



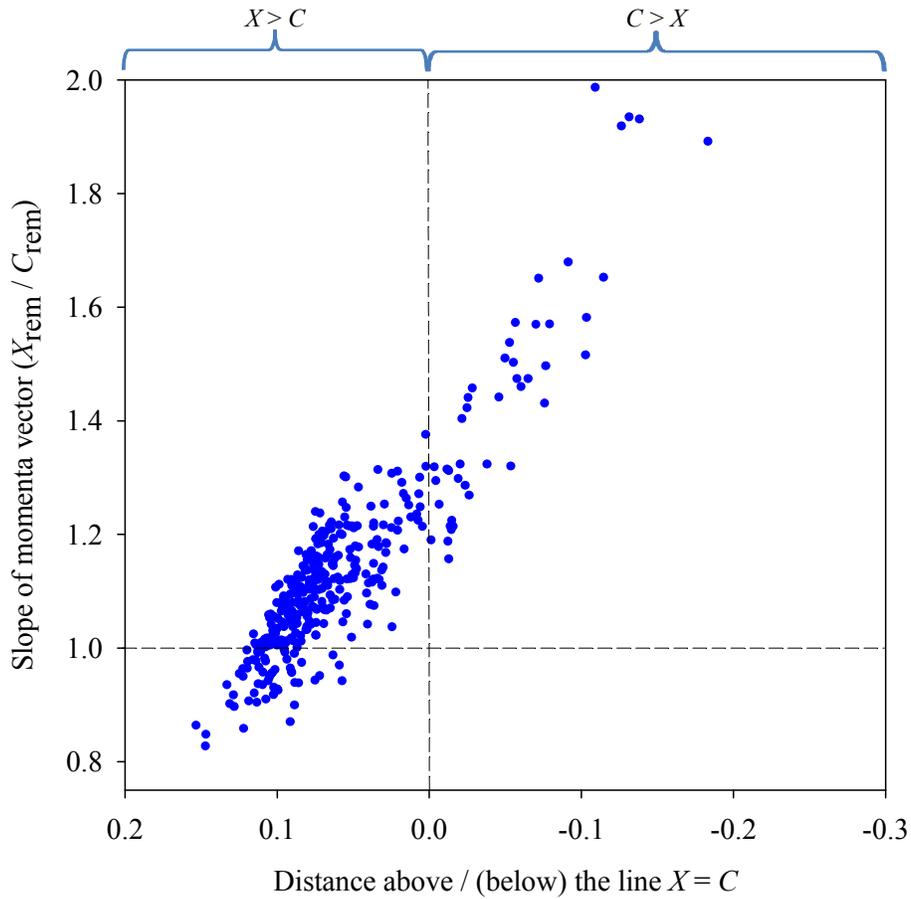
**Figure 3. To which is a city closer – the creative or non-creative economy?** Each city ( $n = 364$ ) for each year 2005 thru 2013 is plotted. Cities above the line  $x = y$  are closer to the non-creative economy while those below  $x = y$  are closer to the creative economy. Red = cities that are always closer to the non-creative economy, green = cities that are always closer to the creative economy, and blue = cities that cross the boundary over time.



**Figure 4. Number of specializations vs. *C*.** Each dot represents a city for one of the years 2005-2013. As the list of a city's specialty occupations grows, and its workforce becomes more diverse, so does the city's Creative Jobs Index *C*.



**Figure 5. The  $X_{rem}-C_{rem}$  vector of each MSA in 2013.** All cities that are already closer to the creative economy (below the line  $C = X$ ) have momentum vectors with slope  $> 1$ , meaning that they are being pulled more strongly towards the non-creative economy.



**Figure 6. Slope of a city’s momentum vector vs. the city’s distance from the line  $X = C$ .** Regarding the x-axis, recall in Figure 5 that the line  $X = C$  divides cities into those that are closer to either the non-creative or creative economies. Thus, cities whose distance to  $X = C$  is positive are closer to the non-creative economy while those whose distance is negative are closer to the creative economy. Regarding the y-axis, cities with a momentum slope  $> 1$  are pulled more strongly towards the non-creative economy and those with slope  $< 1$  are pulled more towards the creative economy. As cities get closer to the creative economy, they experience an ever greater pull back towards the non-creative economy.

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