Hierarchy and Concentration in the American Urban System of Technological Advance*

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Abstract

This article investigates aspects of the urban hierarchy and concentration of patent sub-categories in United States metropolitan areas by estimating Zipf, Gini, and Moran's *I* coefficients. Results do not support a power law depiction of the location of disaggregate patenting in the entire metropolitan system. Analysis of patent sub-categories' upper tails provides useful information on urban-based systems of invention leadership. Patent technologies vary in concentration across the urban system. Results show that the most concentrated and hierarchical patent technologies are computer hardware and software, computer peripherals, information storage, communications, surgery and medical instruments, nuclear and x-rays, semiconductor devices, optics, and organic compounds. Technologies are cross-classified by the sizes of their upper tail Zipf coefficients and Gini measures of concentration. This sorting reveals aspects of variety in locational patterns and offers clues into systems of knowledge exchange in urban-based technological advance.

JEL classification: C2, D39, O3, O51, R1

Key words: agglomeration, concentration, invention, patents, Zipf's law

1 Introduction

Invention and innovation drive economic growth and often stem from ideas that partly develop from knowledge acquired from nearby sources (Grossman and Helpman 1991; Aghion and Howitt 1992; Anselin et al. 1997; Fischer and Varga 2003; Rosenthal and Strange 2004; Verspagen and Schoenmakers 2004; Agrawal et al. 2008; Ponds and Van Oort 2008; Miguelez et al. 2010). Access to knowledge is heightened when experts in similar and related technological fields are proximal, mobile, and interconnected (Glaeser et al. 1995; Fujita and Krugman 2004). Cities are conducive environments for invention because they ease interaction between skilled professionals who engage in knowledge transfer (Glaeser and Mare 2001; Rosenthal and Strange 2004). As accessibility enhances technological advance, creative activities geographically cluster to reduce the friction of distance that may encumber knowledge sharing (Audretsch and Feldman 1996; Audretsch 1998; Porter 1998; McCann and Simonen 2005; Sonn and Storper 2008).

Many studies have explored the geography of knowledge creation enterprises (Verspagen and Schoenmakers 2004; Moreno et al. 2005; Alecke et al. 2006), yet analysis of the locational properties of technologically disaggregate invention in the U.S. remains largely underexplored. The objective of this paper is to investigate several aspatial and spatial distributional properties of different technological inventions across U.S. metropolitan areas and to summarize and compare concentration intensities. Invention exceeds population concentration across metropolitan areas (Ó hUallacháin 1999; Varga 1999; Lim 2003; Liu and Sun 2009; Breschi and Lenzi 2010). Disproportionate concentration partly arises from evolutionary reasons such as firm spin-offs from parent companies resulting in uneven geographical entrance (Sorenson and Audia 2000; Oinas and Malecki 2002; Buenstorf and Klepper 2009; 2010). The positive influence of network and population density on knowledge generation and exchange also plays a role (Saxenian 1994; Knudsen et al. 2008). Dispersion forces attenuate agglomeration. Dense settlements invoke agglomeration diseconomies through congestion (Duranton and Puga 2004; Glaeser and Kohlhase 2004; Horner 2004) including high rents, traffic (Tabuchi 1998; Higano and Shibusawa 1999), pollution (Zheng 1998; Wheeler, 2003), disease (Maliszewski and Wei 2011), and damage from natural and human-made disasters (Maliszewski and Horner 2010; Maliszewski and Perrings 2012). Zipf, Gini, and Moran's *I* coefficients are estimated for thirty-six patent sub-categories (Hall et al. 2002). These measures permit sorting of sub-categories by urban hierarchical configuration and geographical concentration.

Our main finding is that patent sub-categories differ in concentration levels across cities and in the upper tails of their urban system distributions. The most concentrated patents in these upper tails include computer hardware and software, computer peripherals, information storage, communications, surgery and medical instruments, nuclear and x-rays, semiconductor devices, optics, and organic compounds. The main policy relevance of the results is that they allow comparison of technologies by locational concentration, upper tail hierarchy, and implied strength of knowledge flows. Economic development policies that foster knowledge creation by enhancing human capital, advancing technical problem solving, and accelerating corporate start-ups and spin-offs, require a high degree of urban focus that varies across technologies.

The article is organized as follows. Section 2 describes our methodology. Section 3 details the data used in the analysis. Section 4 provides results followed by a discussion and conclusions in section 5.

2 Methodology

Glaeser et al.'s (1992) distinction between knowledge flows that occur within industries (Marshall 1890; Arrow 1962; Romer 1986; Porter 1990—MAR externalities) compared with those that occur between industries (Jacobs 1969) has led to an extensive literature on the character of knowledge flows (Audretsch 1998; Acs and Varga 2005, Baldwin and Martin 2005; Varga 2006; Agrawal et al. 2010). However, what is important to note, is not that knowledge flows between one firm/industry or many firms/industries, but that knowledge exchange is enhanced by propinquity or more generally accessibility. Spatial proximity transcends industrial diversity and competition—closeness is of general overarching importance and cities help to provide this leverage.

Research within organizational ecology argues that clustering occurs in industries where spin-off and parent companies are closely associated (Sorenson and Audia 2000; Oinas and Malecki 2002; Buenstorf and Klepper 2009; 2010). This clustering is strongly influenced by relational knowledge networks that contain a good deal of intertemporal dependence. An evolutionary perspective proposes that spin-off entrepreneurs often locate near their parent company following a period of knowledge acquisition as employees. In contrast, network theory views clustering as an outcome of complex knowledge flows in local relational networks (Glaeser et al. 1992). Inventive activities cluster because they exploit and enhance knowledge flows.

These relationships have prompted considerable scholarly interest in the geography of knowledge-related activities (see Jaffe et al. 1993; Feldman and Florida 1994; Acs et al. 2002; Thompson 2006; Fornahl and Brenner 2008). Audretsch and Feldman (1996), for example, concluded that production clustering is highest in innovative industries that gain the most from knowledge externalities. Invention precedes innovation, but its driving mechanisms and relationship with the urban system are not clear-cut. Henderson et al. (1995) and Audretsch and Feldman (1996) argued that the strength of knowledge flows varies across industries. Some inventions are highly knowledge intensive and need immediate access to new insights. Advance in other technologies is less influenced by close interaction among inventors. The former perhaps includes semiconductor and biotechnology inventions that are inherently novel and heavily reliant on state-of-the-art research and development (R&D) and easy access to science and engineering knowledge. In contrast, technologies underlying textiles or husbandry, for example, are not characteristically cutting-edge. These technologies change slowly, they rely far less on immediate access to novel ideas, and, in turn, are not as dependent on urban agglomeration. An objective of this article is to elucidate the most concentrated technologies, suggesting potentially greater reliance on face-to-face knowledge exchange. This sorting helps classify technologies on the basis of concentration and the nature of their hierarchical organization in the national urban system.

A useful way to measure distributional hierarchy is to estimate the slope of a linear logarithmic rank-size distribution (Berry 1961; Krugman 1996). These scaling or power-law parameters can be estimated for each patent sub-category. If the mathematical specification of a power law is logarithmically transformed into a linear model, and the estimated slope is absolute 1, the distribution follows Zipf's law. In these hierarchies, the majority of some quantity amasses in a few observations (Newman 2005). The derived slope estimates, also known as Zipf coefficients, reveal a higher (or lesser) degree of hierarchy in technology-specific distributions.

Power laws occur in many social and physical distributions (Auerbach 1913; Zipf 1949; Guérin-Pace 1995; Okuyama et al. 1999; Newman 2005; Batty et al. 2008; Batty 2009) and explanations abound (Gabaix 1999; Okuyama et al. 1999; Newman 2005; Batty 2008). Newman (2005) attributed power laws to the Yule process, or a "rich get richer" mechanism contributing to advantages for those observations at the top of the hierarchy. In this explanation, power laws are driven by a dynamical process, in which a system is "set-off" and "locked-in" to propulsion once it passes some critical point in time and space. In contrast, Okuyama et al. (1999), Batty (2008), Batty et al. (2008) and Batty (2009) argued that the occurrence of Zipf's law is partially driven by resource limitations in intensely competitive systems. If patent sub-categories follow Zipf's law, these theories can perhaps lead to better understanding of knowledge-based external scale economies.

Zipf's law is:

$$p_i = C / r_i^{\alpha} \tag{1}$$

in which p_i is the quantity associated with observation *i*; r_i is the rank of observation *i* according to its value p_i among observations *i*, *C* is a constant (i.e. *C* = p_i when r_i = 1), and α is the concentration exponent ($0 < \alpha < \infty$). For technology *t*, we ranked each metropolitan statistical area (MSA) *i* by its share of patents *p* from largest to smallest. Equation (1) is transformed into a standard linear regression equation (2) for each sub-category:

$$\ln p_{it} = \ln C_t + \alpha_t \ln r_{it} \tag{2}$$

in which p_{it} is the patent count of observation *i* in technology *t*, r_{it} is the rank of observations *i* in technology *t*, C_t is a constant or *y*-intercept of each *t*; α_t is the estimated slope or Zipf coefficient of each *t*. Equation (2) is estimated for each *t* using Ordinary Least Squares (OLS).

We follow Batty et al. (2008) who regress size on rank to estimate the scaling parameters and plot size on the *y*-axis and rank on the *x*-axis to display the distributions. This gives greater weight to the larger metropolitan areas in each sub-category and the associated plots are easier to interpret. We are primarily interested in the upper tails of each sub-category because entire distributions are not linear and big centers generate most of the patents. Eliminating small observations makes OLS regression more suitable (Batty et al. 2008; Newman 2005). Adding a quadratic term to tackle nonlinearities generates multiple coefficients, which risks confounding sub-category sorting. The upper tail of each distribution provides the most useful information on patent hierarchy. The steeper the plot of the upper tail, the greater the scaling parameter, and the greater the concentration of patents a few large centers. Often scholars investigating Zipf's law regress rank on size to capture lower tail distributional characteristics, since that tail is the usual origin of change (Batty 2009). Our purpose is to explore distributional hierarchies in cross-sections and not to investigate longitudinal change. We plot r_t and p_t as $\ln r_t / \ln r_t^{\max}$, $\ln p_t / \ln p_t^{\max}$ for all *t* such that each axis is standardized by their maximum rank and patent-size values. All rank and size values are arranged from 0 to 1 for visual overlay and direct comparison (see Figure 1). With a logarithmic transformation and this standardization, a straight diagonal line of plotted observations occurs if a power law is extant.

Beyond assessing patent hierarchy, we calculate patent concentration across U.S. metropolitan areas. Measuring concentration can be elusive given the diverse array of available measures and related definitional challenges. The Gini coefficient is a well-known approach to measuring distributional concentration and is widely used in analysis of inequality (Gini 1912; Kuby and Reid 1992). This coefficient is expressed as:

$$G_t = \left(\frac{N}{N-1}\right)\left(\frac{1}{2}\sum_{i=1}^{N}\left|\hat{p}_{it} - x_{it}\right|\right) \tag{3}$$

in which N is the number of MSAs, $\hat{p}_{it}$ is the percentage of patents generated in the i^{th} MSA and t^{th} technology, x_{it} = 1/N and is the expected percentage of patents in a category from MSA i if the distribution is completely homogenous for technology t. A perfectly even distribution has a zero Gini coefficient following standardization by N/(N-1). Total concentration in a single observation yields a value of unity. Without standardization, total concentration has a value of 1-(1/N).

The Gini coefficient is sometimes adjusted to tackle biases in the organization of the underlying data. Ellison and Glaeser (1997) modified the Gini coefficient in analysis of employment concentration by weighting it with the Herfindahl index to account for differences in firm size. This adjustment is unnecessary in analysis of patent data composed of invention counts by individuals. A potential snag would arise if a single inventor has an exceedingly large share of patents in a sub-category, but this does not occur. Gini coefficients are locationally invariant and ignore the underlying spatial distribution of the observations (Dawkins 2004; Rey and Folch 2011). Moran's *I* measures spatial clustering (Moran 1950). Positive and significant Moran's *I* coefficients occur when neighboring values in space are more similar to each other compared with observations that are far apart. Significantly negative values are observed when neighbors are dissimilar. Insignificant Moran's *I* coefficients occur when the spatial distribution has no pattern. Moran's *I* is:

$$I_t = \left(N \Big/ \sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}\right)\left(\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}(p_{it} - \bar{x}_t)(p_{jt} - \bar{p}_t) \Big/ \sum_{i=1}^{N}(p_{it} - \bar{p}_t)^2\right) \tag{4}$$

in which w_{ij} is a binary spatial weight such that w_{ij} = 1, if MSAs i and j are considered neighbors, 0 if not, p_{it} is the associated attribute value (i.e. patents) for technology t in MSA i, $\bar{p}_t$ is the mean value of p for technology t, and N is the number of observations.

Selection of spatial weights is critical in applying and calculating Moran's *I*. Weights are mostly based on contiguity, *k*-nearest neighbors, or distance-based properties. Since many MSAs are spatial islands, contiguity weights are inappropriate. In this article, we use a distance of 75 miles to define the weight matrix. Anselin et al. (2000) noted that across American MSAs this threshold is a reasonable approximation of the maximum distance an individual will travel in a day to engage in face-to-face interaction.

3 Data

The study area is the metropolitan U.S. within the forty-eight contiguous states. Owing to their spatial isolation, we exclude Alaskan and Hawaiian MSAs. Patent counts, averaged over the period 1995-1999, are used as proxies for urban invention, which were compiled by the United States Patent and Trademark Office (U.S. Patent and Trademark Office 1999). The place of residence of the first named inventor ties patents to MSAs. Consolidated Metropolitan Statistical Areas for large complex urban population centers and Metropolitan Statistical Areas for the remaining urban centers are the observations. The total number of MSAs is 275. Patents are organized into 36 technological sub-categories made available by Hall et al. (2002). They recognized that aggregating patents into groups of sub-categories is challenging, which advises caution in interpreting the results.

Many inventions are patented (Mansfield 1986) and associated tallies are widely used indicators of knowledge activity (Varga 1999). Patented inventions must pass rigorous inspection and meet minimum originality and commercial applicability standards. Acs and Audrestch (1989) and Acs et al. (2002) viewed patents as useful proxies for innovations. Patent awards are highly correlated with corporate research and development expenditures (Griliches 1990) and are better predictors of innovation compared with academic research expenditures (Jaffe 1989; Furman et al. 2002; Bee 2003). In short, patents are useful indicators of national, regional, and urban technological advance (Scherer 1984; Audretsch 1995). Patents also have limitations. Not all novel contrivances are patented, some are not commercialized, and firms may strategically patent to deter competitor entry (Mansfield 1986; Griliches 1990). Patents vary in commercial value and the award process sometimes fails to weed out trivial inventions. Employment counts are alternative indicators of knowledge-based activity, but job numbers in disaggregated sectoral classification schemes are frequently suppressed to protect firms' privacy. Moreover, employment is a proxy for industrial production and not technological advance. Patent records are accessible, classification schemes are flexible, and are closer to knowledge generation compared with most other measures (Jaffe et al. 1993; Hall et al. 2002).

4 Results

Table 1 shows the estimated Zipf, Gini, and Moran's *I* coefficients, the percentage of total patents in the top twenty percent of MSAs, and the top five MSAs ranked by shares of patents in each sub-category. R^2 goodness-of-fit values are listed directly below each Zipf coefficient. The logarithmic rank-size distributions of most technologies t across all areas are non-linear. Estimations of quadratic forms—not reported—support this finding. Non-linearity signals that the distributions, across all metropolitan areas, do not follow Zipf's law. Moreover, using OLS to derive estimates of the slope coefficients using all observations is unreliable. To tackle this concern without confounding the analysis, we report only the upper tail Zipf coefficients by eliminating observations with standardized logarithmic ranks greater than one-half ($\ln r_t / \ln r_t^{\max} > 0.5$). These upper tail Zipf coefficients are shown in Table 1 and are used in the cross-classification of technologies.

[Insert Table 1 here]

The upper tail estimated Zipf coefficients range from -0.409 in gas to -1.200 in optics with an average value of -0.75. While most distributions do not strictly follow a power law in their upper tails, several sub-categories approximate Zipf's law including: computer peripherals (α = -0.995); communications (α = -0.951); information storage (α = -0.912); computer hardware and software (α = -0.908); semiconductor devices (α = -0.936); motors, engines and parts (α = -1.018); earth working and wells (α = -0.912); miscellaneous chemical (α = -0.942); and miscellaneous drugs and medical (α = -0.908). R^2 goodness-of-fit values are well above 0.9. Optics has an upper tail primate distribution with a Zipf coefficient of -1.20. Its largest center, Rochester (NY), garners over three times more awards compared with New York that is ranked second. Although computer peripherals' Zipf coefficient is almost 1.0, its largest, San Francisco, is more than triple the size of its second largest center, Rochester (NY). Similar primacy of the largest (San Francisco) compared with the second largest (Boise) center occurs in semiconductor devices. In motors, engines and parts the largest (Detroit) generates more than three times as many patents as the second largest (Los Angeles) center. Houston is the preeminent center of earth working and wells generating over 28 percent of patents, which is approximately triple the number of second ranked Dallas.

The smallest Zipf coefficients occur in coating (-0.529), gas (-0.409), resins (-0.552), biotechnology (-0.519), heating (-0.578), and pipes and joints (-0.594). These technologies' intermediate centers generate more patents than would occur if Zipf's law prevailed. In biotechnology, for example, San Francisco is the largest center, but in the next tier -- New York, Boston, Washington DC, and San Diego—patent numbers are similar across centers. Intermediate centers in gas and heating also generate comparable patent numbers. Other examples of sub-categories with strong intermediate metropolitan areas include electrical devices, power systems, materials processing and handling, and receptacles, with Zipf coefficients of -0.686, -0.683, -0.624, -0.609, respectively.

Some technologies have above average Zipf coefficients. These sub-categories often have dominant centers in the first and second rank that are noticeably more inventive compared with the next tier. Examples of leading pairs include New York/San Francisco in communications (-0.951) accounting for 23.57 percent of the sub-categories' patents, New York/Los Angeles generate 23.74 percent of miscellaneous drugs and medical's (-0.908) patents, and New York/Philadelphia in organic compounds (-0.853) with 25.95 percent of patents. Surgery and medical instruments (-0.820) has four dominant centers (San Francisco, Los Angeles, New York and Minneapolis) and electrical lighting (-0.724) is robust in San Francisco, Los Angeles, and New York. Furniture and house fixtures has a small Zipf coefficient, with the design centers of Los Angeles and New York equally dominant.

Figure 1A-F shows the logarithmically transformed rank-size distributions of each technological sub-category. The sub-categories are aggregated into categories according to the Hall et al. (2002) classification scheme for effective visualization. The figure shows the assignment of sub-categories to categories and standardization, as discussed above, permits visual comparison. Category averages condense characteristics of similar technologies. Chemicals have an average Zipf coefficient of -0.64 and are the least and computers and communications are the most hierarchical with an average coefficient of -0.94. The drugs and medical and electrical and electronic categories match the overall average across all groupings with Zipf coefficients of -0.74. Mechanical technologies have an average Zipf of -0.84 and others average -0.69, which suggests relatively weak hierarchy. The plots help visualize several aspects of the distributions, especially variation within a category and the dominance of the largest centers. Mechanical, for example, has the widest variety. The dominance of large centers in several technologies is conspicuous in several plots including communications, surgery and medical instruments, electric lighting, materials processing and handling, earth working and wells, and furniture and fixtures.

[Insert Figure 1 here]

Table 1 also shows the estimated Gini coefficients, which average 0.84 and range from 0.756 in agriculture, husbandry and food to 0.949 in semiconductor devices. All 275 metropolitan areas are included in these calculations. Other low Gini's occur in materials processing and handling (0.765), transportation (0.794), miscellaneous mechanical (0.784), furniture and house fixtures (0.786), heating (0.792), and miscellaneous others (0.782). Inventions in these technologies are relatively spread across the urban system and are generated in most metropolitan areas. Beyond semiconductors, computer hardware and software (0.905), computer peripherals (0.924), information storage (0.945), and optics (0.925) have high Gini's. These concentrated technologies are limited to fewer metropolitan areas. Semiconductor devices, for example, are generated in only 104 areas.

Several sub-categories are significantly spatially clustered—positive Moran's *I* with 75 mile spatial weights. Those significant at the 0.05 level include surgery and medical instruments, miscellaneous drugs and medical, amusement devices, apparel and textiles, furniture and house fixtures. Information storage, computer peripherals, optics, communications, biotechnology, electrical lighting, motors, engines and parts, receptacles, measuring and testing, materials processing and handling, and miscellaneous mechanical are significantly clustered at the less convincing 0.10 level. The remaining technologies have spatial distributions that are not significantly different from one generated by a random process. We acknowledge that these results are most likely sensitive to adoption of the Anselin et al. (2000) 75 mile spatial weight.

Finally, Table 1 lists the principal MSAs of each technological sub-category. New York and San Francisco dominate most technological patent sub-categories. New York ranks first in 14 and San Francisco leads in 13 sub-categories. The latter is more dominant in the technologies its heads. New York only exceptional position is in drugs. New York generates seventeen percent of drug patents with second placed Philadelphia accounting for ten percent. The gaps between the first and second ranked areas, in which New York is first, are much smaller. New York has a diverse technological base ranking in the top five metropolitan areas in all but two technological sub-categories (information storage and pipes and joints). San Francisco is more preeminent in most of the technologies it leads, especially computer hardware and software, computer peripherals, information storage, biotechnology, electrical devices, measuring and testing, nuclear and x-rays, power systems, and semiconductor devices. Detroit ranks first in four sub-categories related to the automotive industry, including metal working, motors, engines and parts, transportation, and pipes and joints. Two specialized small areas are major patent generators including Rochester (NY) that accounts for 32 percent of optics inventions and Boise, (ID) that ranks second after San Francisco in information storage and semiconductor devices. Houston's preeminence in generating earth working and wells patents is tied to its natural resource—oil and gas—economic base.

4.1 Concentration classification of patent technologies

Hierarchy and concentration are not equivalent. A technology, for example, can have a small Zipf with a relatively large Gini coefficient. In that case, dominance at the top of the hierarchy is shared by several large centers with other areas participating far less. In short, the estimated Zipf and Gini coefficients permit a four-way classification of sub-categories by hierarchy and concentration. Patent technologies are sorted by greater or lesser than the average Zipf coefficient (in absolute terms) and by greater or lesser than the average Gini coefficient. The resulting classifications are organized as a Carroll trilateral diagram (Carroll 1896) in Table 2, which allows incorporation of Moran's *I* coefficients in the sorting.

Patent technologies with above average Gini and Zipf coefficients are concentrated across MSAs and have strong hierarchical configurations in the upper tails of their urban distributions. We term this group *cardinal technologies*, which includes computer peripherals, information storage, communications, computer hardware and software, surgery and medical instruments, nuclear and x-rays, semiconductor devices, optics, and organic compounds (see Table 2). Surgery and medical instruments, communications, optics, computer peripherals, and information storage are the only *cardinal technologies* that are significantly spatially clustered (i.e. neighboring metropolitan areas with significantly similar levels of patenting). These technologies are concentrated at the top of their distributions that are limited to relatively few areas.

Patent sub-categories with below average Gini and Zipf coefficients are more evenly distribution across MSAs and have weaker upper tail hierarchical configurations. We term these *ubiquitous technologies*, which include: gas; coating; heating; pipes and joints; apparel and textiles; agriculture, husbandry and food; measuring and testing; power systems; materials processing and handling; metal working; furniture and house fixtures; receptacles; miscellaneous mechanical; and miscellaneous others. In contrast to *cardinal technologies,* the *ubiquitous technologies'* weaker concentration, especially in their upper tails, suggests less dependence on face-to-face knowledge flows in a few critical metropolitan areas. *Ubiquitous technologies* are perhaps less concentrated because they underpin a broad set of other technologies and critical knowledge flows are tied to Jacobs and not MAR externalities.

An above average Zipf and a below average Gini coefficient identifies patent technologies that are concentrated in their upper tails with a good deal of uniformity in intermediate and smaller places. In other words, these patents are generated by inventors across many metropolitan areas, but certain areas prevail at the top of their urban hierarchy. We term these hierarchical *ubiquitous technologies* including motors, engines and parts, transportation, earth working and wells, amusement devices, miscellaneous drugs and medical and miscellaneous chemical. These technologies have several critical centers but they also participate in technological advance in an assortment of other specialties located across the urban system.

Finally, some technologies have below average Zipf and above average Gini coefficients. These sub-categories have upper tails that are not particularly hierarchical, but they are relatively concentrated across the urban system. We term these technologies *regime technologies,* which include agriculture, food, and textiles, resins, drugs, biotechnology, electrical devices, electrical lighting, and miscellaneous electrical and electronic. These focused technologies are not as dependent on location at the top of their respective hierarchies compared with *cardinal technologies* that particularly concentrate in their largest areas. Biotechnology patents, for example, are concentrated in the urban system but they have more leading centers compared with semiconductor devices.

[Insert Table 2 here]

5 Conclusions

Network and evolutionary theories advance understanding of knowledge flows and associated urban agglomeration of inventive activities. We set out in this article to compare hierarchical configurations and concentration levels of distinct patent groupings in the American urban system of technological advance. Varying locational patterns suggest varying reliance on deep and immediate knowledge flows in rapidly changing science and engineering specialties. Advance in computer and medical related technologies, for example, need local access to knowledge flows generated by skilled professionals. Geographical concentration is sustained by distance sensitive face-to-face interactions. In contrast, more evenly distributed technologies suggest far less dependence on intense and specialized knowledge flow. Some technologies are underpinned by industries founded on a localized natural resource.

Results do not support a power law depiction of the location of patenting in the entire American metropolitan system. However, analysis of patent sub-categories' upper tails provides useful information on urban-based systems of invention leadership. Measures of concentration provide additional insights, especially inequality and spatial clustering in patenting across the entire urban system. Combining these measures permits cross-classification of technologies and evokes better understanding of unobserved knowledge flows. Results show that computer peripherals, information storage, communications, computer hardware and software, surgery and medical instruments, nuclear and x-rays, semiconductor devices, optics, and organic compounds are the most concentrated technologies in the upper tail of their metropolitan distributions. The high degree of concentration of these *cardinal technologies* suggests heavy reliance on knowledge flows in a small number of critical centers. Economic development policies seeking to foster growth in specific technologies must focus on a handful of centers. We also identified several technologies that are far less hierarchical and concentrated ranging from receptacles and measuring and testing patents to coating and power systems. These *ubiquitious technologies* are less reliant on location in a few specialized cities suggesting association with Jacobs external economies of scale. We also identified *hierarchical ubiquitous technologies,* including motors and engine, which are relatively widespread, but also have focus on a few dominant centers. Finally, *regime technologies*, including drugs and biotechnology, are concentrated but not particularly focused in the upper tails of their distributions. The existence of several major centers suggests less dependence on local knowledge flows compared with the *cardinal technologies*. We recognize that our classification scheme should be interpreted with caution, since it is difficult to categorize inventive technologies by rigidly distinctive groupings. Nonetheless, our results show that patent technologies vary in focus on the upper tails of their locational distributions and in concentration levels. Diversity in these patterns is consistent with the notion that cutting-edge technologies are embedded in assorted systems of knowledge exchange in urban agglomerations.

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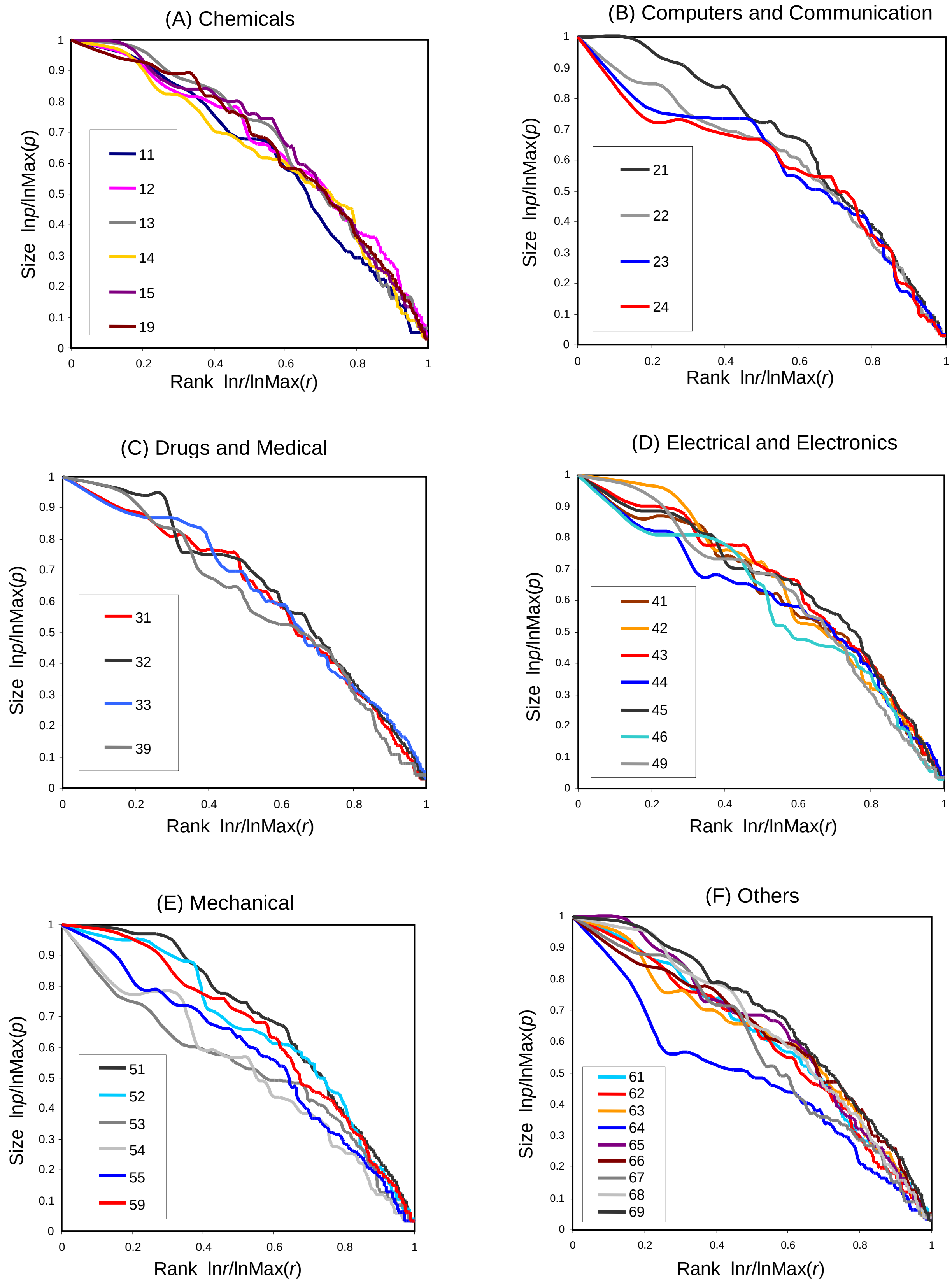
Figure 1.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15
19
(B) Computers and Communication
Size lnp/lnMax(p)
Rank lnr/lnMax(r)
21
22
23
24
(C) Drugs and Medical
Size lnp/lnMax(p)
Rank lnr/lnMax(r)
31
32
33
39
(D) Electrical and Electronics
Size lnp/lnMax(p)
Rank lnr/lnMax(r)
41
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49
(E) Mechanical
Size lnp/lnMax(p)
Rank lnr/lnMax(r)
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(F) Others
Size lnp/lnMax(p)
Rank lnr/lnMax(r)
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Table 1.

Sub-Category Code	Sub-Category Name (Number of MSAs with patents)	Coefficient			Percentage of total patents in top 20 percent of MSAs (excluding zeros)	MSA	Percentage of total patents
		Zipf (R^2)	Gini	Moran's I			
11	Agriculture, Food, Textiles (*n* = 148)	-0.603 (0.961)	0.848	0.007	88.39 (76.48)	New York Philadelphia Atlanta San Francisco Los Angeles	10.45 8.67 6.54 5.56 4.40
12	Coating (*n* = 185)	-0.529 (0.962)	0.839	0.009	88.50 (79.83)	San Francisco New York Philadelphia Los Angeles Minneapolis	10.03 8.15 5.43 4.53 4.32
13	Gas (*n* = 136)	-0.409 (0.943)	0.832	0.008	86.72 (70.90)	New York Minneapolis San Francisco Buffalo Allentown	7.42 6.93 5.38 4.89 4.48
14	Organic Compounds (*n* = 165)	-0.853 (0.991)	0.877	0.030	92.66 (83.55)	New York Philadelphia San Francisco Chicago San Diego	14.38 11.57 6.06 5.48 4.26
15	Resins (*n* = 172)	-0.552 (0.962)	0.871	0.015	91.79 (84.56)	Philadelphia New York Houston San Francisco Cleveland	10.11 9.40 5.67 4.54 4.45
19	Miscellaneous Chemical (*n* = 260)	-0.942 (0.947)	0.824	0.024	86.82 (85.91)	New York San Francisco Rochester, NY Los Angeles Philadelphia	10.17 7.17 6.43 5.23 5.18
21	Communications (*n* = 224)	-0.951 (0.985)	0.886	0.075*	93.43 (90.96)	New York San Francisco Chicago Los Angeles Dallas	11.86 11.71 7.83 6.69 5.05
22	Computer Hardware and Software (*n* = 203)	-0.908 (0.975)	0.905	0.014	94.90 (92.00)	San Francisco New York Austin Los Angeles Seattle	24.51 9.06 7.85 4.53 3.53

Table 1. (*Continued*)

Sub-Category Code	Sub-Category Name (Number of MSAs with patents)	Coefficient			Percentage of total patents in top 20 percent of MSAs (excluding zeros)	MSA	Percentage of total patents
		Zipf (R^2)	Gini	Moran's *I*			
23	Computer Peripherals (*n* = 123)	-0.995 (0.938)	0.924	0.042*	96.93 (88.38)	San Francisco Rochester, NY Seattle New York Portland, OR	24.55 7.51 5.93 5.72 5.65
24	Information Storage (*n* = 106)	-0.912 (0.921)	0.945	0.037*	98.67 (91.09)	San Francisco Boise Austin Dallas Denver	33.37 6.73 6.40 5.26 4.70
31	Drugs (*n* = 196)	-0.693 (0.970)	0.894	0.035	93.38 (89.54)	New York Philadelphia San Francisco Boston Washington, DC	17.02 9.60 7.76 5.24 5.24
32	Surgery and Medical Instruments (*n* = 236)	-0.820 (0.839)	0.858	0.090**	90.23 (88.21)	San Francisco Los Angeles New York Minneapolis Cincinnati	12.21 10.04 8.51 8.32 2.99
33	Biotechnology (*n* = 174)	-0.519 (0.935)	0.892	0.081*	92.66 (87.01)	San Francisco New York Boston Washington, DC San Diego	15.99 8.87 7.47 7.47 6.56
39	Miscellaneous Drugs and Medical (*n* = 174)	-0.908 (0.963)	0.849	0.174**	88.41 (81.40)	New York Los Angeles San Francisco Minneapolis San Diego	13.04 10.70 6.80 6.07 3.59
41	Electrical Devices (*n* = 206)	-0.686 (0.933)	0.856	0.031	90.42 (84.69)	San Francisco Chicago New York Los Angeles Dallas	14.08 6.92 6.89 6.07 5.60
42	Electrical Lighting (*n* = 186)	-0.724 (0.929)	0.871	0.101*	91.04 (84.95)	San Francisco Los Angeles New York Chicago Phoenix	11.95 10.68 9.29 6.14 4.00

Table 1. (*Continued*)

Sub-Category Code	Sub-Category Name (Number of MSAs with patents)	Coefficient			Percentage of total patents in top 20 percent of MSAs (excluding zeros)	MSA	Percentage of total patents
		Zipf (R^2)	Gini	Moran's *I*			
43	Measuring and Testing (*n* = 206)	-0.646 (0.971)	0.837	0.061*	88.34 (83.11)	San Francisco Los Angeles New York Detroit Houston	10.65 6.72 6.23 5.56 3.44
44	Nuclear and X-rays (*n* = 154)	-0.753 (0.969)	0.876	0.027	92.27 (83.37)	San Francisco New York Los Angeles Boston Washington, DC	17.22 7.89 6.91 3.67 3.67
45	Power Systems (*n* = 207)	-0.683 (0.955)	0.831	0.052	88.31 (82.35)	San Francisco Los Angeles New York Detroit Chicago	10.71 6.10 5.80 5.10 4.04
46	Semiconductor Devices (*n* = 104)	-0.936 (0.909)	0.949	0.006	98.68 (90.05)	San Francisco Boise Dallas New York Austin	29.09 9.98 8.78 8.69 7.47
49	Miscellaneous Electrical and Electronic (*n* = 195)	-0.729 (0.946)	0.862	0.046	90.45 (85.86)	San Francisco New York Los Angeles Chicago Dallas	12.84 10.53 7.52 4.37 3.49
51	Materials Processing and Handling (*n* = 254)	-0.624 (0.934)	0.765	0.077*	81.11 (79.66)	New York Los Angeles Detroit Chicago San Francisco	5.88 5.65 5.10 5.08 4.65
52	Metal Working (*n* = 216)	-0.741 (0.867)	0.809	0.039	85.82 (80.53)	Detroit New York San Francisco Los Angeles Chicago	8.12 6.58 6.50 5.42 4.77
53	Motors, Engines and Parts (*n* = 223)	-1.018 (0.946)	0.815	0.052*	85.92 (82.26)	Detroit Los Angeles Chicago Peoria, IL New York	21.00 6.23 4.77 3.16 2.43

Table 1. (*Continued*)

Sub-Category Code	Sub-Category Name (Number of MSAs with patents)	Coefficient			Percentage of total patents in top 20 percent of MSAs (excluding zeros)	MSA	Percentage of total patents
		Zipf (R^2)	Gini	Moran's *I*			
54	Optics (*n* = 150)	-1.200 (0.947)	0.925	0.021*	95.56 (90.11)	Rochester, NY New York San Francisco Los Angeles Philadelphia	32.03 9.15 9.06 8.21 3.13
55	Transportation (*n* = 249)	-0.775 (0.991)	0.794	0.041	82.66 (81.02)	Detroit Los Angeles New York Chicago San Francisco	13.42 8.61 4.51 4.23 3.35
59	Miscellaneous Mechanical (*n* = 261)	-0.675 (0.968)	0.784	0.075*	82.55 (81.44)	New York Los Angeles Detroit Chicago San Francisco	8.43 7.62 6.39 5.20 3.71
61	Agriculture, Husbandry, Food (*n* = 246)	-0.734 (0.988)	0.756	0.008	78.84 (67.37)	New York Chicago Los Angeles Minneapolis San Francisco	9.41 6.89 5.00 4.53 3.37
62	Amusement Devices (*n* = 230)	-0.768 (0.986)	0.822	0.196**	86.08 (83.48)	Los Angeles New York Chicago San Francisco Sarasota	13.09 8.81 6.34 4.30 4.05
63	Apparel and Textile (*n* = 226)	-0.655 (0.956)	0.804	0.098**	84.77 (80.91)	New York Los Angeles Chicago San Francisco Philadelphia	11.40 8.46 3.99 3.96 3.06
64	Earth Working and Wells (*n* = 200)	-0.912 (0.897)	0.841	0.009	86.78 (82.08)	Houston Dallas Los Angeles New York Tulsa	28.27 9.71 3.04 2.89 2.51
65	Furniture, House Fixtures (*n* = 251)	-0.674 (0.942)	0.786	0.095**	82.63 (81.01)	Los Angeles New York Detroit Chicago San Francisco	8.96 8.88 5.75 4.87 3.78

Table 1. (*Continued*)

Sub-Category Code	Sub-Category Name (Number of MSAs with patents)	Coefficient			Percentage of total patents in top 20 percent of MSAs (excluding zeros)	MSA	Percentage of total patents
		Zipf (R^2)	Gini	Moran's *I*			
66	Heating (*n* = 192)	-0.578 (0.988)	0.792	0.047	83.39 (74.58)	New York	8.76
						Los Angeles	5.29
						Chicago	4.75
						Detroit	3.93
						San Francisco	3.88
67	Pipes and Joints (*n* = 175)	-0.594 (0.949)	0.820	0.052	84.69 (74.95)	Detroit	11.25
						Houston	7.44
						Chicago	7.00
						Los Angeles	5.82
						San Francisco	4.06
68	Receptacles (*n* = 242)	-0.609 (0.908)	0.804	0.053*	84.46 (81.88)	New York	9.70
						Los Angeles	8.13
						Chicago	7.29
						St. Louis	4.50
						Atlanta	3.90
69	Miscellaneous Others (*n* = 271)	-0.716 (0.968)	0.782	0.060	82.87 (82.55)	New York	8.04
						Los Angeles	7.41
						San Francisco	6.20
						Chicago	4.73
						Minneapolis	4.19

Source of technological categorization: Hall et al. (2002); *Source of patents*: U.S. Patent and Trademark Office (1999).
Note: Moran's *I* spatial weights are defined by a minimum distance threshold—75 miles—with no self neighbors.
*Significant at the $p < 0.1$ level.
**Significant at the $p < 0.05$ level.

Table 2.

	Above average Gini coefficient (Concentrated)	**Below average Gini coefficient (Ubiquitous)**
Above average Zipf's α **(Hierarchical)**	*Cardinal Technologies* Computer Hardware and Software Organic Compounds Nuclear and X-rays Semiconductors Surgery and Medical Instruments Communications Optics Computer Peripherals Information Storage **Significant**	*Hierarchical Ubiquitous Technologies* Transportation Earth Working and Wells Misc. Chemical Amusement Devices Misc. Drugs and Medical Motors, Engines, Parts **Moran's *I***
Below average Zipf's α **(Non-hierarchical)**	*Regime Technologies* Biotechnology Electrical Lighting Agriculture, Food, and Textiles Resins Drugs Electrical Devices Misc. Electrical and Electronic	*Ubiquitous Technologies* Receptacles Apparel, Textiles Furniture/House Fixtures Measuring & Testing Materials Processing and Handling Misc. Mechanical Gas Heating Coating Pipes and Joints Power Systems Agriculture, Husbandry, Food Misc. Others

*Technological sub-categories outside the center square have insignificant Moran's *I* coefficients.