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Invention in the city: Increasing returns to patenting as a scaling function of metropolitan size

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Abstract

We investigate the relationship between patenting activity and the population size of metropolitan areas in the United States over the last two decades (1980–2001). We find a clear superlinear effect, whereby new patents are granted disproportionately in larger urban centers, thus showing increasing returns in inventing activity with respect to population size. We characterize this relation quantitatively as a power law with an exponent larger than unity. This phenomenon is commensurate with the presence of larger numbers of inventors in larger metropolitan areas, which we find follows a quantitatively similar superlinear relationship to population, while the productivity of individual inventors stays essentially constant across metropolitan areas. We also find that structural measures of the patent co-authorship network although weakly correlated to increasing rates of patenting, are not enough to explain them. Finally, we show that R&D establishments and employment in other creative professions also follow superlinear scaling relations to metropolitan population size, albeit possibly with different exponents.
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1. Introduction[2]

Inventors and innovators do not operate in isolation; the creation of new ideas is a process that very often involves the integration and recombination of existing knowledge originating from different individuals, locations, institutions and organizations (Lenski, 1979; Mokyr, 2002; Fleming, 2001). The size, density and compactness of urban centers foster interpersonal interactions, thus creating greater opportunities for enhanced information flows. As a result, historically cities have been the places where much innovation has occurred. The privileged role that cities have played in the development of science and technology, and more broadly, in the generation of inventions and

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innovations – intellectual and material, cultural and political, institutional and organizational – has been well documented by historians, urbanists, geographers, anthropologists and regional economists (Mumford, 1968; Pred, 1973; Jacobs, 1984; Hawley, 1986; Bairoch, 1988; Mokyr, 2002; Braudel, 1992; Hall, 1998; Feldman and Audretsch, 1999; Redman, 1999; Varga, 1999; Spufford, 2003; Algaze, 2005).

More recently the role of cities as centers for the integration of human capital and as incubators of invention was rediscovered by the "new" economic growth theory, which posits that knowledge spillovers among individuals and firms are the necessary underpinnings for growth (Romer, 1986, 1990; Lucas, 1988). As Glaeser (1996) points out, the idea that growth hinges on the flow and exchange of ideas leads naturally to the recognition of the social and economic role of urban centers in furthering intellectual cross-fertilization. Moreover, this process is self-reinforcing. The creation and concentration of knowledge in cities increases their attractive pull for educated, highly skilled, entrepreneurial and creative individuals who, by locating in urban centers, contribute in turn to the generation of further knowledge spillovers (Feldman and Florida, 1994; Glaeser, 1999; Florida, 2002, 2004). This seemingly spontaneous process, whereby knowledge produces growth and growth attracts knowledge, is the engine whereby urban centers sustain their continuous development through unfolding innovation.

It is therefore a compelling question to ascertain which features of urban societies foment, or hinder, invention and innovation. To step in this direction we need quantitative measures of innovation. Historical evidence notwithstanding, it is not easy to measure knowledge spillovers (a problem discussed by Krugman (1991)). This difficulty hampers progress towards the quantitative understanding of the relationship between urban characteristics and innovation. Some knowledge flows do nevertheless leave an evidentiary trail in the form of patented inventions (Acs and Audretsch, 1989; Malerba and Orsenigo, 1999; Jaffe et al., 2000; Jaffe and Trajtenberg, 2002).[3]

Patenting in the United States is and has always been largely an urban phenomenon, from the earliest stages of the nation's industrialization in the 19th century (Pred, 1966; Feller, 1971; Higgs, 1971; Sokoloff, 1988) and continuing during the first half of the 20th century (Ullman, 1958; Thompson, 1962). More recent studies have confirmed the importance of a metropolitan setting for the inventive process. Jaffe et al. (1993), in an examination of patent citations by new to previously issued patents, find that new patents are 5–10 times more likely to cite previous ones originating from the same metropolitan area. O'hUallachain (1999) confirmed that most of the patents issued in the United States are awarded to residents of metropolitan areas. Acs et al. (2002) also find that patenting in the United States is overwhelmingly concentrated in metropolitan counties, while Carlino et al. (2005) reaffirm that large metropolitan size and high metropolitan density favor patenting.

Based on this evidence we expect a close and positive relationship between city size and inventive activity.[4] Higher concentrations of individuals and firms in larger cities can be expected to sustain a larger repertoire of intellectual capabilities, thereby facilitating the creation and recombination of ideas. This environment in turn attracts creative individuals and firms to locate in cities thus sustaining a "virtuous" cycle of invention and innovation.[5] In the present discussion, we investigate the quantitative relationship between patenting activity and the size, measured in terms of population, of metropolitan areas in the United States over the last two decades. In particular, we will seek to identify whether this relationship is an instance of a general scaling relation. Issues of scaling are deeply involved in the study of systems whose macroscopic behavior emerges from general micro-level interactions among the system's constituent units (Chave and Levin, 2003). As discussed further on, a scaling relationship between metropolitan size and inventive activity is indicative of general organizational principles replicated across different metropolitan areas, of different sizes.

It is only a slight exaggeration to say that the most important attribute of a city is its size; it matters, because it is the most obvious and all encompassing manifes-

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[3] We are well aware of the criticism that patents are not necessarily good indicators of generic innovative activity since not all new inventions are patented, and many economically important types of innovations (for example a musical theme, an architectural design, a children's story, an advertising campaign, a business model or computer software) cannot even be patented (Griliches, 1979, 1990; Pakes and Griliches, 1980). While these caveats make us cautious about the use of patent data and prudent in the interpretation of our results, we nevertheless see patents as the "footprints" of some (by no means all) inventive activity.

[4] We will use the term "inventor", in a rather restrictive way, to refer to those individuals who have been granted a patent for their invention. As in Kuznets (1962) we see "inventive activity" being concerned with technical inventions, involving the creation of new knowledge and the combination of existing knowledge.

[5] This expectation is a variant of the familiar argument that increases in urban scale generate greater positive externalities (Marshall, 1890; Jacobs, 1969).

tation of a city's success at attracting and maintaining financial and human capital and engaging it in a myriad of competitive and interdependent activities. It is in this sense that measures of invention and innovation should scale positively with city size. We recognize from the onset that cities differ not only in size but also in the characteristics of their populations. Boston, for example, has a large population of academics, researchers and technical workers, while proportionally New York City has less, and Los Angeles less still. Although such considerations are important for a detailed understanding of each metropolitan area, in the present discussion we ask if there are average characteristics of cities that make them centers of inventive activity. The expectation is that if larger cities are more inventive, then there should be an average trend for measures of invention to increase with city size. The quantification of this relationship clarifies if larger population agglomerations give rise to increasing rates of invention that are simply proportional to population, or if instead there are increasing returns to scale.

In order to address questions about the nature and magnitude of the scaling relationship between metropolitan invention and population we use data for patents granted in the United States between 1980 and 2002, spatially aggregated into metropolitan statistical areas (MSAs). Specifically we use patent data to single out individual inventors and patent co-authorship as a source of relational information. In this way, we render the location-specific networks of collaboration among inventors visible and measurable, and inquire into their effects on inventive activity. Economic sociologists argue that economic interactions cannot be fully understood without paying attention to the social relationships in which they are embedded (c.f., Polanyi, 1957; Granovetter, 1985; Uzzi, 1996; White, 2002; Swedberg, 2003; Zuckerman, 2003). Analogously we can argue that the process of invention cannot be well understood without paying attention to the social interactions among inventors (Arora and Gambardella, 1994; Powell et al., 1996; Walker et al., 1997; Orsenigo et al., 2001). Social networks play an important role in the diffusion of information and knowledge since they provide the formal connections and informal linkages through which ideas flow among individuals.[6] These knowledge spillovers

often occur without the mediation of market mechanisms, transcend the institutional and workplace settings in which individuals operate, and cut across organizational boundaries.[7] By mapping patent co-author relationships, we can investigate whether structural features of metropolitan networks of inventors can help explain the quantitative scaling relationship between metropolitan patenting and population.[8]

The remainder of this paper is organized as follows. The next section discusses what is distinctive and interesting about scaling relationships. Section 3 describes the U.S. patent data, how it was used to identify metropolitan inventors and networks of inventors, and the details of how it was spatially aggregated and matched with metropolitan population data. Section 4 presents our econometric estimations for the dependence of patents on metropolitan size, while Section 5 tests whether features of the co-authorship networks among inventors help explain the observed scaling between patenting and population. It may be expected that the relationship between patenting and metropolitan size is part of a more general relationship between R&D, and even "creative" activities, and metropolitan scale. Such relations are quantified in Section 6. Section 7 concludes with a discussion of our findings, their clear and potential consequences, and maps out directions for further research.

2. Scaling and self-similarity

Although several measures of correlation can be explored when studying urban invention, scaling has a particular meaning. Scaling relations parameterize how a given quantity of interest Y depends on a measure of the size of the system N (Brock, 1999). In what follows N will be the number components in a complex social system, such as the population of a city. When Y obeys a scaling relation with N, it satisfies on average:

$$Y = cN^{\beta}. \tag{1}$$

The significance of this "power law" relation becomes more evident when we consider that it is the solution to the equation:

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[6] Social networks have been highlighted as an important facet of regional innovation (see, e.g., Piore and Sabel, 1984; Breschi and Lissoni, 2001; Owen-Smith and Powell, 2004) and are believed to be the conduits for transferring knowledge and ideas between firms in a region. Much of Silicon Valley's success, for example, has been attributed to its informal networks of friendship and collaboration among its scientists, engineers, and entrepreneurs (Saxenian, 1994).

[7] Scientists, especially those working in fields where commercial exploitation is common or expected, do, however, also exchange information on a market basis (see Zucker et al., 1998).

[8] For examples of using patent co-authorship data as evidence of knowledge spillovers and to construct social networks, see Murray (2002), Newman (2000), Balconi et al. (2004) and Fleming et al. (2004).

$$Y(\lambda) = \lambda^\beta Y(N), \tag{2}$$

for arbitrary $\lambda > 0$. This equation expresses the relation between Y for a system of size N, to Y for a system λ times larger. The existence of scaling implies that such a relationship – the ratio $Y(\lambda N)/Y(N)$ – is parameterized by a single number β, usually referred to as the scaling exponent. In particular $Y(\lambda N)/Y(N)$ is independent of the system size N; it is only dependent of the ratio between sizes λ. This property is referred to as scale invariance, or self-similarity, across scales. If, for example, the rate of patenting is a scaling function of urban size, then the number of new patents generated by city of 10 million will stand in the same proportion to those generated by a city of one million, as the number of patents generated by the latter relative to those crated by a city of 100,000, and so on.

As remarked by Barenblatt (2003), "...scaling laws never appear by accident. They always manifest a property of a phenomenon of basic importance...the phenomenon, so to speak, repeats itself on changing scales." (p. xiii). Such repetition is almost always a hint that there are underlying dynamical processes that generate and maintain the same relationship among structural and functional variables over the range of the scale—typically many orders of magnitude. This is the essence of self-similarity (Brown et al., 2000). In this sense, as suggested by Chave and Levin (2003), "...scaling concepts offer an avenue to study heterogenous assemblies for which the microscopic processes are not know, and probably not knowable (e.g., in the case of social systems) except in terms of their statistical properties." (p. 551). Thus scaling relations, or "laws", are perhaps the best and most extraordinary evidence for the existence of general features in the immensely complex dynamics of social and economic systems. Examples of scaling relationships in the socio-economic realm include the well-known "Zipf's Law", which states that a city's size decreases in inverse proportion to its rank among other cities within the same urban system (Zipf, 1949; Makse et al., 1995); the (rank) size distribution of firms (Steindl, 1965; Ijiri and Simon, 1977; Amaral et al., 1997); the distribution of executive compensation (Walls, 1999); "Pareto's Law" for the distribution of personal income (Mandelbrot, 1963), and the rate of crime in American cities (Glaeser and Sacerdote, 1999).[9]

Establishing the existence of scaling phenomena for cities is thus an extremely tempting goal, as it would indi-

cate the existence of social mechanisms at play across an entire urban system, integrating together in single swoop all complexities of interactions among the individuals, households, firms, and institutions living, residing and operating in these spaces. Moreover, the successes or failures of particular urban centers are only meaningfully assessed relative to these general trends, common to the entire urban system in which they are embedded. Below we will be concerned with the existence and quantification of inventive activity in metropolitan areas, proxied by rates of patenting, as well as several other associated quantities.

Methodologically, we apply a power law functional form to the relationship between a measure of inventive activity, Y, and metropolitan size:

$$Y_{i,t} = \alpha N_{i,t}^\beta, \tag{3}$$

where Y denotes, for example, patenting output or inventive employment in the ith metropolitan area at time t (in units of a year), N refers to metropolitan population, and α and β are both constants. Specifically we use the following as our basic econometric estimation equation:

$$\ln Y_{i,t} = \alpha + \beta \ln N_{i,t} + \varepsilon_{i,t}, \tag{4}$$

with ε as Gaussian white noise. The utter simplicity of the straight line conveys the striking result of self-similarity: as the size of the metropolitan area changes, the relationships among its different components and processes must adjust so that the relationship between size and inventive output is maintained. If we find that inventive activity behaves superlinearly ($\beta > 1$) with respect to metropolitan size, it exhibits increasing returns to scale. The exponent $\beta = 1$ implies that inventive activity scales linearly, *i.e.*, proportionally, to metropolitan population. Finally if $\beta < 1$, inventive activities scale sublinearly, exhibiting decreasing returns to scale. Thus, the quantification of scaling relations in terms of β allows us to determine whether larger cities are more innovative, equally innovative or less innovative per capita than smaller cities.

3. Metropolitan patenting

Source data was extracted from the U.S. Patent Office (USPTO) records on all granted U.S. patents from 1980 to 2001 (U.S. Patent Office 2003). Every patent includes all inventors' last names (with varying degrees of first and middle names or initials), each inventor's home town, detailed information about the patent's technology in class and subclass references (over 100,000 subclasses exist), and the discrimination of the owner, or assignee,

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[9] For a review of scaling analysis in economics see Brock (1999) and Stanley and Plerou (2001).

of the patent (generally a firm, and less often a university, if not owned by the inventor). Patent filings do not, however, provide consistent listings of inventor names or unique identifiers for the authors. Since the USPTO indexes source data by patent number and not by inventor, a variety of conditional matching algorithms were used to identify inventors, each inventor's patents and other inventors with whom the focal inventor has co-authored at least one patent.[10] The final database includes 2,058,823 unique individual inventors and their patent co-authors, and a total of 2,862,967 patents.

By identifying individual inventors, matching inventors with patents, assigning a location to each inventor – specifically a metropolitan statistical area (MSA) – and linking inventors who have co-authored a patent, it is possible to construct patent co-authorship networks for 331 MSAs in the continental United States. (An MSA includes a core city and surrounding counties, which together form a local labor market area.) Patent co-authorship refers to the situation where a patent is either applied for by more than one individual or lists more than one individual as a designated inventor (we will use the terms "co-authorship", "co-patenting", and "co-inventing" interchangeably). Every inventor's hometown was matched to a zip code, which was then assigned to an MSA using the ZIPList5 dataset.[11] County level population data was extracted from the Bureau of Economic Analysis' "Regional Economic Accounts Tables" (which are available online at http://www.bea.doc.gov). Counties were assigned to MSAs according to the MSA definitions used to create the metropolitan inventor networks. The analyses presented here relied upon all patents with at least one inventor within a metropolitan area. Thus, if inventors from inside and outside an MSA co-authored the same patent, the patent would appear in each inventor's metropolitan area. The networks are constructed anew for each year on the basis of the new patents granted that year.

An examination of the summary statistics for various measures of metropolitan patenting is revealing, and perhaps, intriguing (see Table 1). The variables patents (denoting new patents assigned to metropolitan-based inventors) and inventors (signifying the number of metropolitan-based individuals listed as co-authors in newly granted patents) are both characterized by a negative binomial distribution (a Poisson distribution with over dispersion). As a consequence, these two variables exhibit great variation, as indicated by the coefficient of variation, across metropolitan areas. This variation, combined with the skewness characteristic of the negative binomial distribution, hints at one of our main results, namely, that patenting is disproportionably concentrated among the largest metropolitan areas. The mean for both variables increased from 1980 to 2001 (and did so every year in the 22 year span), reflecting the increase in patenting activity during the 1980s and 1990s. The mean for patents per capita, often referred to in the literature as "patent intensity", the number of patents per 1000 metropolitan inhabitants, also increased steadily during the period covered by the data, providing additional evidence for acceleration in patenting rates. (The behavior of inventors per capita, not reported in the table, behaved similarly to patents per capita.)

Surprisingly these increases in patenting rates are not due to higher productivity. A simple measure of metropolitan inventive productivity, patents per inventor, the ratio of new patents to the total number of inventors; steadily and significantly decreased between 1980 and 2002. A similar picture is conveyed by another measure: patenting team size, that is, the number of inventors associated with a patent. This variable was calculated for every patent in the database and then averaged across metropolitan areas (see Table 1). The metropolitan mean for average patenting team progressively increased from 1980 to 2001 and the variable's relatively small coefficient of variation indicates that this was the common trend across metropolitan areas.[12] Examining the behavior of patenting team size as well as the proportion of total metropolitan patents authored by single inventors (referred to as single inventor patents in Table 1) indicates that patenting became an increasingly collective activity over the 22 years from 1980 to 2002. The common trend across U.S. urban systems over the last two decades has been for the number of metropolitan patents and inventors to quickly increase, but this change was also associated with a steady decrease in inventive productivity per inventor and recourse to larger patenting collaborations.

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[10] The matching procedures, discussed in detail in Fleming et al. (2004), refine the previous approach of Newman (2000).

[11] Ziplist5 (http://www.zipinf.cm) is a commercially available dataset containing every active ZIP code currently defined by the U.S. Postal Service for the entire USA. Every zip code is assigned to an MSA if the zip code lies within a metropolitan county. The MSA county definitions used by ZIPList5 are consistent with the Census Bureau's 2000 MSA definitions.

[12] The correlation between the metropolitan average for patenting team size and metropolitan population is very low, in the order of 0.09 every year, suggesting that the increase in the size of inventor teams was not a location-specific phenomenon.

Table 1
Summary statistics for metropolitan variables

Year	Patents	Inventors	Patents per capita	Patents per inventor	Patenting team size	Single inventor patents	Connectivity	Density	Clustering	LC size	R&D employment	Supercreative professions
1980											1987	
Mean	689.82	633.29	0.97	1.03	1.64	0.509	733.75	0.02	0.43	0.10	949.65	
S.D.	1472.1	1274.38	0.91	0.22	0.27	0.213	1276.21	0.03	0.21	0.11	2095.20	
CoV[a]	2.13	2.01	0.94	0.21	0.16	0.42	1.74	1.50	0.49	1.10	2.21	
Median	175	182	0.69	1.01	1.62	0.52	109	0.01	0.45	0.06	122	
Min	3	2	0.03	0.57	1	0	1	0	0	0.01	0	
Max	12,990	10,220	5.78	2.49	2.89	1	7813	0.11	0.87	0.64	13,637	
Number of MSAs	331	331	331	331	331	331	331	331	331	331	227	
1990											1997	
Mean	858.33	955.11	1.14	0.88	1.92	0.418	1262.80	0.04	0.59	0.11	1146.08	
S.D.	1690.91	1823.79	1.02	0.16	0.33	0.193	2370.26	0.06	0.23	0.15	3611.90	
CoV[a]	1.97	1.91	0.89	0.18	0.17	0.46	1.88	1.50	0.39	1.36	3.15	
Median	243	284	0.82	0.86	1.91	0.41	233	0.02	0.62	0.06	133	
Min	2	2	0.02	0.47	1	0	3	0	0	0.08	8	
Max	12,882	12,594	6.16	1.55	3.13	1	15,717	0.33	1.01	0.68	34,853	
Number of MSAs	331	331	331	331	331	331	331	331	331	331	266	
2000											2002	1999–2001[b]
Mean	1724.24	2069.19	2.06	0.79	2.52	0.377	4638.05	0.05	0.81	0.15	1280.52	36,985.47
S.D.	3753.69	4217.39	2.61	0.18	0.45	0.215	8620.60	0.07	0.14	0.16	3952.58	70,483.01
CoV[a]	2.18	2.04	1.27	0.23	0.18	0.57	1.86	1.40	0.17	1.07	3.09	1.91
Median	424	557	1.34	0.77	2.51	0.33	637	0.02	0.83	0.09	146	13,420.17
Min	6	10	0.06	0.42	1.33	0	39	0	0.43	0.15	9	296.67
Max	38,170	37,051	13.09	2.93	4.02	1	58,014	0.25	1.11	0.80	38,000	541,033.33
Number of MSAs	331	331	331	331	331	331	331	331	331	331	278	331.00

[a] CoV, coefficient of variation.
[b] Yearly variable values averaged over this period.

4. Metropolitan patent co-authorship networks

What part of the invention process is captured by the co-authorship links between metropolitan inventors? What do these links imply in terms of information flow and the possible effects of such flows upon subsequent inventive productivity? Singh (2004) reports significant flow of information between patent co-authors, as measured by citations from future patents that are linked by direct – and even indirect – collaborative ties. The results hold even after econometrically controlling for the greater likelihood of a citation arising simply because it refers to work in similar technologies. Singh goes on to demonstrate that almost all of the geographical citation "spillovers" in the United States (e.g., Jaffe et al., 1993) result from co-authorship networks. (Breschi and Lissoni (2004) find similar results for European inventors.) Thus, agglomeration of connections among inventors can be expected to increase inventiveness if connectivity indeed enhances information flow and knowledge spillovers.

Even if we see the links forged by inventors in the act of co-inventing as possible channels for knowledge spillovers, we also echo the cautionary remark made by Hussler (2004), who, using terminology from Hur and Watanabe (2001), views the spillovers evidenced by patents as "intentional spillovers". Inventors are often very selective in what prior knowledge they chose to cite as relevant to their invention.[13]

A metropolitan co-authorship network of inventors includes isolated "nodes" (inventors who are the sole authors of patents), small clusters of inventors connected to each other through shared co-authorship, and larger-sized components grouping many metropolitan inventors together. Individual clusters and components are often linked through key individuals (with high degree of "betweenness") who have connections to multiple inventive communities. We will invoke four simple graph-theoretic descriptions of networks – connectivity, density, clustering and the size of the largest component – when exploring the impact of inventor network structure on the scaling relationship between metropolitan patenting and population. Connectivity is simply a measure of how many connections, or ties, there are in the network. The higher this measure is, the greater the number of patenting collaborations present within a metropolitan

area. Conversely, for fixed number of nodes the higher the measure the more inventors there are linked to each other. As discussed above it seems plausible, a priori, to assume there is a close relationship between connectivity and patenting rates. The average density of connections among inventors in the network is defined as the actual number of ties, L, divided by the potential number of ties between N nodes (*i.e.*, density = $L/(N(N-1))/2$). The naïve expectation is that more highly connected and denser networks will have greater flows of information among inventors thereby making the inventors in such networks more productive.

In order to define average network clustering we follow Watts and Strogatz (1998) and first calculate individual clustering for each node as the number of actual "triples" for each inventor (*i.e.*, the number of different pairs of an inventor's collaborators that have worked with one another and are therefore linked). Inventors with one or zero ties receive a clustering score of zero. This single node clustering is then averaged over the whole set of inventors within an MSA. We further normalized this number to produce an averaged MSA clustering coefficient by dividing the average node clustering by the theoretical clustering of a random graph of commensurate size, that is, with the same number of inventors, and mean degree (the degree of a node in a graph is the number of edges linked to the node.). Thus clustering is a measure of agglomeration of inventors in the sense that it measures the probability that an inventor connected to another also collaborated with his other co-authors. The largest component of a network is the largest set of inventors that can trace a direct or indirect collaborative connection to one another. The size of the largest component is calculated as the fraction of inventors that had a collaborative tie within the largest component in the MSA. The largest component is thus the largest inventive community within a metropolitan network of inventors and in this sense measures agglomeration effects beyond nearest neighbor.

Glancing at the summary statistics (Table 1) for network density and size of the largest component it is notable how non-dense co-authorship metropolitan inventor networks are, as well as the smallness of the largest component. The averaged number of co-authorship links is systematically very low, between 1 and 2, across time and urban centers. These observations, combined with another – the relatively high level of clustering – provide a first hint that overall network connectivity is not a significant determinant of patenting output. The high clustering levels insinuate a picture of inventors linked to other inventors in small co-authorship groups that therefore will not scale up with city size.

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[13] As discussed by Jaffe et al. (1993), Globerman et al. (2001) and Breschi and Lissoni (2004), the large majority of citations to previous relevant patents ("prior art") are added by patent examiners rather than by the inventors authoring patents.

5. Scaling of metropolitan invention with population size

Our primary interest is to elucidate the nature of the statistical relationship between a metropolitan area's inventive output, measured by the number of new patents granted per year to inventors residing in the corresponding MSA, and the size of its population. Specifically we want to know if there is a general average trend for the increase of invention with metropolitan population size. The use of the term average requires some explanation: we use it here to allow us to intentionally neglect metropolitan specificities. In this sense, by taking many cities with different characteristics, we expect such characteristics to be effectively averaged over. Our interest in scaling leads us to estimate equations without the controls for demographic, social or industry characteristics that we would surely include if our interest instead was to estimate a model for metropolitan patenting (as in Carlino et al. (2005) or Strumky et al. (2005)).

We assume a power law relationship between metropolitan population (N) and newly granted metropolitan patents (P) and use Eq. (4) as our estimation equation.[14] The data on metropolitan population was obtained from the Bureau of Economic Analysis' Regional Economic Accounts (BEA, 2005). We availed ourselves of the richness of a dataset containing cross-sectional and time-series data by estimating the scaling coefficient using a panel data fixed effects feasible generalized least squares (FGLS) framework (assuming heteroskedastic error structure across cross-sectional units (MSAs) and AR(1) serial autocorrelation within cross-sectional units).

The estimated value for the coefficient, model 1 in Table 2, is $\beta = 1.29$ (with a 95% confidence level of $1.26 \leq \beta \leq 1.32$); the adjusted R^2-value of 0.72 indicates a good log-linear fit. We also estimated the exponent β for three individual years, 1980, 1990 and 2000 (using an OLS estimation procedure with a correction for heteroskedasticity): the statistically significant (at the 95% confidence level) coefficient values are, respectively, $\beta = 1.29$, 1.25 and 1.26 with adjusted R^2-values ranging from 0.69 to 0.73.

The scaling relationship between metropolitan population and metropolitan invention is superlinear, or to use the language of economics, the relationship exhibits

[14] Transforming the patent count data using the natural logarithmic function has the effect of changing its distribution into a normal one—as verified both by visual inspection of histograms and by performing the Wilks–Shapiro test (for individual periods and across all periods for all MSAs).

Table 2
Estimation results using a pooled fixed effects FGLS model by metropolitan statistical area, 1980–2001

Dependent variable	(1) Patents	(2) Inventors	(3) Patents	(4) Patents per inventor	(5) Patents	(6) Patents	(7) Patents	(8) Patents
Constant	−10.82	−10.41	0.04	−0.47	5.59	6.02	5.68	
Population	1.291* (0.015)	1.238* (0.014)						
Inventors			0.981* (0.002)					
Patents per inventor				0.028 (0.016)				
Connectivity					0.823* (0.001)			
Size of LC						0.029* (0.004)		
Clustering							0.183* (0.010)	
Density								−0.228* (0.009)
Number of MSAs	331	331	331	331	331	331	331	331
Number of observations	6951	6951	6951	6951	6951	6951	6951	6951
Adjusted R^2	0.72	0.74	0.98	0.12	0.83	0.26	0.38	0.93

All of the variables are in natural logarithmic form. Coefficients marked with an asterisk are significant at the 99% confidence level.

increasing returns to scale (*i.e.*, $\beta > 1$). Not surprisingly, a larger metropolitan population is associated with a greater output of new patents; what is surprising is the magnitude of the increasing returns to scale. On average we can expect a city like Philadelphia, with about 1.5 million people to generate almost 19 times more patents than a city of the size of Eugene, OR or Springfield, MO, which are about 10 times smaller. This finding suggests two alternative explanations: either inventors are individually more productive in a larger city, or there are a disproportionate number of inventors in larger metropolitan areas. In the next section, we investigate which of these effects is at the root of our scaling result.

6. Agglomeration or network effect?

What lies at the origin of the increasing returns of scale of invention with metropolitan size? As anticipated above, we advance and test two alternative hypotheses. The first is that the number of inventors in a city is roughly proportional to population, perhaps supported by the simplistic assertion that each individual has an equal probability to become an inventor, taken together with the expectation that a larger metropolitan population leads to higher inventive productivity, *i.e.*, to more inventions per inventor. In fact, the number of connections generally grows superlinearly with the number of nodes. In the simplest scenario, for example, the total number of connections between N inventors connected all to all grows quadratically with N, as $N(N-1)/2$, setting an upper bound on $\beta \leq 2$. In reality we expect that for large N, not all inventors will connect to all others, and that the number of links should scale with a smaller (but still superlinear) exponent, reflecting constraints on individual time and effort to sustain multiple relationships. In this way by measuring the scaling of connectivity with metropolitan population we may be able to explain the superlinear relation between invention and population, even if the number of inventors remains a fixed fraction of the number of inhabitants across many different MSAs.

The second, alternative, hypothesis is that inventors are not more productive in larger cities but that their numbers increase superlinearly with metropolitan size. This hypothesis is commensurate with a theory of cities as attractors for the "creative class" (Florida, 2002, 2004). In this scenario network effects, although present, are different and more subtle. Indeed it maybe the possibility of other productive relations (financial, cultural, etc.) beyond co-authorship, that will attract an inventor to a city. Then we should not expect a close correla-

tion between co-authorship connectivity measures and patenting rates.

It is also conceivable that the mechanisms underlying the two complementary hypotheses are at play simultaneously. The two pure scenarios (but not their mixture) are easy to distinguish: either the data reveals that the relationship between the number of inventors and population is linear, and the number of patents per inventor versus metropolitan size is superlinear (hypothesis 1), or vice versa (hypothesis 2). In the first case, we further conjecture a close correlation between co-authorship measures of connectivity and patenting rates, whereas such correlation should be weaker if the second scenario is realized.

Regressing the number of metropolitan inventors on metropolitan population, we find that the relationship between the number of inventors and population is clearly superlinear, with a coefficient $\beta = 1.24$ and a 95% confidence interval of $1.22 \leq \beta \leq 1.28$ (model 2 in Table 1). Moreover, the relationship between the number of new metropolitan patents and the number of metropolitan inventors (model 3 in Table 2) is remarkably linear with a coefficient β very close to unity ($0.97 \leq \beta \leq 0.99$). So, indeed more inventors result in more patents, but in a nearly one-to-one relationship, a result that vindicates the second hypothesis. The absence of agglomeration externalities for patenting productivity was already revealed by the summary statistics for the variables patents per inventor and size of the patenting team (discussed in Section 3). Regressing patents per inventor on population size drives the point even further home: the value of the estimated coefficient is 0.028 (see model 4 in Table 2), showing no significant correlation.

What about possible co-authorship network effects? We find that the relationship between the number of metropolitan patents and the level of connectivity of a metropolitan network of inventors is clearly positive but sublinear, with a pooled coefficient of $\beta = 0.82$ (model 5 in Table 2). Thus increasing connectivity, the measure of the extent to which inventors are linked to each other through co-inventing, does not result in proportionately greater patenting output, contradicting the main thrust of the first hypothesis. The effect of increasing the size of the network's largest component, while positive, is well below linear with a coefficient $\beta = 0.26$ (see model 6 in Table 2). The effect of network clustering on patenting is also sub-linear, with a coefficient $\beta = 0.72$ (model 7 in Table 2). The effects on patenting of network density are negligible (model 8 in Table 2).

The combination of these results strongly suggests that, in spite of positive correlations, measures connectivity in co-authorship networks are not related in

any simple way to the scaling of inventiveness with metropolitan size. Instead the simplest scenario for increasing returns in metropolitan patenting rates with population is that they are the result of the self-similar disproportionate presence of more inventors the larger the city, while single inventor productivity stays constant across the entire urban system.

7. The scaling of R&D activities with metropolitan size

Most inventors do not do their inventing in the privacy of their garages. Inventors tend instead to work within organizations and institutions, both public and private, profit and non-profit, which encourage and reward inventive activity. The occasional "accidental" discovery not withstanding, most patenting is the result of concerted effort, by individuals and organizations, requiring a substantial infrastructure and commitment of resources. Patenting is the culmination of successful research—for every patent granted by the U.S. Patent Office there are many applications that are rejected and even more research efforts that failed or dead-ended. Patenting is perhaps better seen as one type of output of an overall research and development effort. All of these considerations suggest that the scaling relationship between patenting and metropolitan size might be an instance of that that between R&D efforts and metropolitan size.

One way to measure research activity at the metropolitan level would be to construct a measure of overall R&D investments by aggregating data on both private and publicly funded research carried out in each metropolitan area. There are, however, severe limitations on the availability of the data needed to construct such a variable. Nevertheless, by using data on private sector R&D employment we constructed what we believe is a proxy measure adequate for our purposes.

In the United States, there are three major sources of R&D funding: university sponsored research, private sector research investments, and Federal government research outlays. Using data provided by the National Science Foundation on research and development funding by "performing sector", we calculated that university sponsored research has averaged only 9% of total R&D yearly expenditures between 1960 and 2003 (U.S. National Science Foundation, 2003). The proportion of all newly granted patents accounted for by university based inventors is equally small—between 1.3% and 3% for every year between 1980 and 2001. From 1960 to 2003 federally provided R&D funding averaged only 12.1% of total yearly R&D expenditures and has

remained below 10% since 1994 (U.S. National Science Foundation, 2003). Inventors based at Federal research laboratories account for a miniscule proportion of newly granted patents, on average, less than 1% a year between 1980 and 2000. Federal and university expenditures on R&D combined represent an average of 22.1% of total yearly research outlays for the period 1960–2003 (U.S. National Science Foundation, 2003). The private sector is by far the most significant source of R&D investments and patents.

The nature of private sector data makes difficult, though, to construct a metropolitan-based measure of private research efforts. Data on private sector R&D expenditures is available for the nation as a whole and at the corporate level for publicly held companies. Corporate level R&D investment data is contained in companies' annual reports but these reports present only total company-wide expenditures undertaken by corporate headquarters. Research and development activities do not often take place in the same locations as corporate headquarters, and a more disaggregated geographic breakdown of research efforts is not typically provided by corporate reporting of R&D efforts. But even if metropolitan-level data on private sector R&D investments is not available, there is data on metropolitan private sector R&D employment. Is the available data a suitable substitute?

There is reason to think that private sector R&D employment closely mirrors private sector R&D investment. The Pearson correlation between total R&D expenditures and national civilian employment of scientists and engineers (Statistical Abstract of the United States, 2005) over the period 1985 and 2003 is 0.97. Data specific to private sector R&D employment is available from the Economic Census for the years 1987, 1992, 1997 and 2002 (this data is described further below); the correlation between private sector R&D employment at the national level and total private sector R&D expenditures for these 4 years is 0.95. The correlation between private sector R&D employment and total R&D investments, for the same set of Economic Census years, is 0.89. These correlations suggest that employment in research and development is a useful proxy for private sector R&D efforts. If we are willing to assume that the strong correlation between private sector R&D investments and private sector R&D employment found at the national level is replicated at the metropolitan level – an assumption made more plausible by considering that labor costs represent the bulk of R&D expenditures – a measure of scientific and technical employment at the level of MSAs would be a statistically suitable stand-in for private sector metropolitan R&D investments.

Table 3
Scaling of metropolitan R&D employment with population (dependent variable: metropolitan R&D employment)

	1987	1997	2002
Constant	−11.37	−12.75	−12.78
Population	1.211 (0.081)	1.174 (0.052)	1.185 (0.050)
Adjusted R^2	0.63	0.67	0.69
Number of MSAs	227	266	278

All variables in natural logarithmic form. Standard errors in parentheses. All of the coefficients are significant at the 99% confidence level.

We assembled data from the Census Bureau's Economic Census for metropolitan employment in private sector establishments engaged in research and development work for the years 1987, 1992, 1997 and 2002. The North American Industrial Classification System (NAICS), used in the 1997 and 2002 Censuses, includes sector 5417, "scientific research & development services", while the Standard Industrial Classification (SIC) system, used in the 1987 and 1992 Censuses includes sector 873, "research, development, and testing services" (U.S. Census Bureau, 1987, 2002) These two categories cover establishments engaged in conducting original investigation undertaken to gain new knowledge (research) and/or the application of research findings or other scientific knowledge for the creation of new or significantly improved products or processes (development). Employment by these two sectors in effect constitute private (*i.e.*, for profit) sector research and development employment. The employment data from the Economic Census was matched to data on metropolitan patenting and population using consistent definitions of metropolitan areas.

We probed the relationship between metropolitan private sector R&D employment and size of metropolitan population by estimating Eq. (4); specifically we regressed the natural logarithm of R&D employment on the natural logarithm of population (using OLS with a correction for heteroskedasticity) with data for the years 1987, 1997 and 2002 (see Table 3). The relationship between private R&D employment and metropolitan population is clearly superlinear with a scaling coefficient significantly greater than one (the 95% confidence interval excludes $\beta = 1$) in each of the 3 years, signifying that larger metropolitan areas also have a disproportionate share of R&D inventive employment. While the adjusted R^2-values for the three estimations are all greater than 0.60, there is greater dispersion of the data around the scaling relationship than for the relationship between inventors and population. This greater dispersion is not surprising given that research and development employment is a more heterogeneous population than inventors—after all not

Table 4
Estimation results for metropolitan "supercreative" employment (data averaged for 1999–2001)

Dependent variable	(1) Supercreatives	(2) Inventors
Constant	−4.97	−4.08
Population	1.147 (0.021)	
Supercreatives		1.082 (0.037)
Number of MSAs	331	331
Adjusted R^2	0.89	0.75

All of the variables are in natural logarithmic form. Standard errors in parentheses. All of the coefficients reported in the table are significant at the 99% confidence level.

every employee of an R&D establishment is engaged in invention.

We were also curious as to whether the superlinear relationship between metropolitan R&D employment and population is replicated using a broader categorization of "inventive" employment. To this end, we examined the statistical relationship between the number of people involved in a select few "creative" professions and the corresponding metropolitan population size, as well as the relationship between creative employment and number of inventors. We adopted Richard Florida's definition of "supercreative" employment, which consists essentially of all scientific, artistic, educational and entertainment professionals (Florida, 2002).[15]

We averaged the data on metropolitan supercreative employment for the 3 years, 1999, 2000 and 2001 (see Table 1 for the summary statistics), and then regressed the natural logarithm of supercreative professionals against metropolitan population (see Table 4). The result

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[15] According to the definition put forward by Florida (2002, pp. 327–329) "supercreative" professions are "Computer and Mathematical, Architecture and Engineering, Life, Physical and Social Science Occupations, Education, Training and Library, Arts, Design, Entertainment, Sports and Media Occupations". The occupational classifications were derived from the Standard Occupational Classification System (SOC) introduced by U.S. Bureau of Labor Statistics in 1998. The SOC classification data is constructed using the North American Industrial Classification System (NAICS). We believe it is reasonable to suppose that most inventors are drawn from these professions.

indicates a clear superlinear scaling relationship between supercreative professionals and metropolitan population size with $1.10 \leq \beta \leq 1.18$ at 95% confidence level and a good liner fit ($\bar{R}^2 = 0.89$). Large metropolitan areas also have a disproportionate share of "supercreative" individuals. The relation between metropolitan inventors and supercreative professionals is in turn approximately linear with $1.01 \leq \beta \leq 1.16$ at 95% confidence level (see Table 4) suggesting that inventors may be a reasonable stand-in for total number of professionals engaged in creative activities, albeit slightly over-represented relative to the more inclusive definition for supercreatives, or vice-versa.

8. Discussion

We started the present inquiry with the objective of quantifying the scaling relationship between metropolitan innovation and population, across cities with very different population sizes as well as many other distinct characteristics. Our statistical results indicate that larger metropolitan areas have disproportionately more inventors than smaller ones and generate more patents according to essentially the same relation. In fact larger cities are tangibly more inventive per inhabitant than smaller ones, thus producing increasing returns in invention to population scale. This property is quantified by exponents $\beta > 1$, characteristic of superlinear scaling in patents (and number of inventors) with population size.

The totality of our results paint a picture of invention where agglomeration – the concentration of inventors in large metropolitan areas – does not increase on average the productivity of the individual inventor. Nevertheless, access to a greater population of inventors could boost the productivity of individuals susceptible to becoming inventors, which would eventually result into a larger number of inventors. In this case, however, average inventive productivity among established inventors does not increase. In this sense, we cannot distinguish whether any impact of agglomeration on inventiveness arises from attracting disproportionately more inventors to an area or by boosting the inventiveness of proto-inventors who were already in the area.[16]

Most likely in our opinion there are a range of informal interaction effects, not captured by co-patenting links but present in a larger population, that lead to the tendency for inventive professionals to concentrate disproportionately in larger metropolitan spaces. The choice made by major innovators and inventors, whose skills and expertise make them highly mobile, to remain in a given metropolitan area indicates that something about the structure of these regions matters (Almeida and Kogut, 1994, 1997). The location-specific characteristics typically mentioned as important in this regard include the tendency of large firms (and especially their R&D labs) to locate in the larger cities and the critical mass of well-educated individuals also to be found there, both of which were explored here. The presence of an (informal) social network of inventors in a metropolitan area could itself play an important, if difficult to measure, role in attracting inventors to an area.

Gell-Mann (1994, p. 97) attributes to Mandelbrot the admission that "early in his career he was successful in part because he placed more emphasis on finding and describing power laws than on trying to explain them". We are in good company then and believe that our manifestly empirical investigation, which sought to identify and describe scaling phenomena in the realm of urban invention, is a useful exercise. But we do recognize that the fundamental question left open for future work is to explain the identified scaling relationships quantitatively, by integrating them into a predictive theory of endogenous (population and economic) growth. At a qualitative level we have shown that there are good indications of a connection between the size of a city and its pull on intellectual capital. Larger cities are also disproportionately the seats of R&D institutions which, either as the cause or the effect, help support a range of innovative activities. Finally while we do not find a convincing link between co-authorship network properties and the relationship between patent output and metropolitan size, we have shown tentative indications that numbers of inventors and patents may be symptoms of a much larger, if more tenuous, self-similar phenomenon. As it has been true for as long as there have been cities, creative human capital resides disproportionately in larger cities.

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