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Agglomeration and the Spatial Distribution of Creativity[1]

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ABSTRACT

This paper analyzes the spatial distribution of "creativity" -- the production of new knowledge. We analyze commercial patents granted in Sweden during 1994-2001 using a panel of one hundred labor market areas which encompass the entire country. We relate patent activity to measures of localization and urbanization, to the industrial composition and size distribution of firms, and to the regional distribution of human capital. Our analysis confirms the importance of human capital and research facilities in stimulating regional patent output. Importantly, our results document the importance of agglomeration and spatial factors in influencing creativity: Patent activity is increased in larger and more dense labor markets and in regions in which a larger fraction of the labor force is employed in medium-sized firms. Our results also indicate that creativity is greater in labor markets with more diverse employment bases and in those which contain a larger share of national employment in certain industries, confirming the importance of urbanization and localization economies in stimulating creativity. Our quantitative results suggest that the urbanization of Sweden during the 1990s had an important effect upon the aggregate level of patent activity in the country, leading to increases of up to five percent in aggregate patents.

JEL codes: O31, N34, R11

Keywords: Agglomeration, patent, spatial distribution, creativity

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I. Introduction

It is widely reported that agglomerations of economic activity in space lead to increased productivity and enhanced economic output. Early evidence, based upon production functions, established that output per worker is higher in urban regions that are larger and denser (e.g., Shefer, 1973). A variety of explanations are offered for these regularities, ranging from better functioning labor markets in larger, denser environments, to Marshallian external economies of scale in production, to the increased possibilities for the division of labor in larger conurbations. (See Quigley, 1998, for a review.)

In this paper, we trace the relationship between the size, density, scale, and specialization of economic regions and "creativity" -- the production of new knowledge in those regions. We measure creativity by the award of patents for commercial innovations in Sweden. We measure patents for a panel of one hundred Labor Market Areas in Sweden which cover the entire country, over an eight year period. We also measure the economic characteristics of these labor market areas, including the industrial composition of the region, the human capital of the workforce, and the intensity of research and development activity in the region.

We pay special attention to the spatial character of each region -- the density of economic activity, the scale of each region, and the extent of industrial concentration or diversity of each of these labor market areas. We find that the density and scale of regional activity matter greatly in the incidence of creativity, so measured. We also find that there are large returns, as measured by patents, to the diversity of regional economic activity. At the same time, we find that there are returns to the concentration of specialized industries in a small number of labor market areas.

Section II below provides a selective review of the literature on the determinants of patent activity. Section III describes the data and our general hypotheses. Section IV reports our principal results and considers their robustness. Section V is a brief conclusion.

II. A brief literature review

Alfred Marshall (1898, 1920) first drew attention to the economic effects of agglomeration and to scale economics external to an individual firm but internal to an industrial district or cluster. He argued that the colocation of firms increased output and the productivity of inputs. Externalities flowing from inputs of human capital in a spatial context had a scientific revival with the endogenous growth models of Romer (1986, 1990), Lucas (1988), and Grossman and Helpman (1991). Griliches (1979, 1998), Anselin, *et al* (1997), and Acs (2002) have modeled this effect in a simple production function at the regional level using local industrial and university research as inputs. Each of these studies reported a significant and positive effect of research in particular university research, on output; this is generally interpreted as evidence of knowledge transfers arising from, or mediated by, the university.

As Marshall and later Krugman (1991), Feldman (1994), Jaffe, *et al* (1996), Audretsch and Feldman (1996), and others have emphasized, space itself forms a barrier to the diffusion of knowledge. Daily face-to-face contact may be quite important in the diffusion of results from scientific research and development (R&D). It is thus beneficial for commercial developers to locate close to universities and other centers of basic research. However, geographic proximity to other firms in the same industry may be of even greater importance in stimulating applied research and innovations which improve practice.

Work by Glaeser, *et al* (1992) and by Henderson, *et al* (1995) documents the link between spatial concentration of economic activity, economic growth, and productivity in U.S. cities. Glaeser, *et al*, conclude that economic diversity (fostering "Jacobs-type" externalities) is more important in affecting economic growth. Henderson, *et al*, distinguish between the growth of high tech industries (for which Jacobs-type externalities are important) and capital goods industries (for which economic specialization is more important.)

Varga (1998) investigated the importance of agglomeration in the production of new knowledge in the U.S. He measured research output using more than four thousand product innovations recorded in 1982. As inputs, he measured annual expenditures for research in American universities as well as the number of employees in laboratories and research institutes within private companies. He then related the number of product innovations to annual expenditures for university research, finding that important returns to scale and scope exist. Varga concluded that there is a critical mass relating scale and scope to the output of innovative activity and to the density and size of a region.

Several analyses of the importance of firm location and knowledge infrastructure have been undertaken in Sweden. Lundquist (2001) analyzed cross sectional data for Sweden for 1996, finding little or no statistical relationship between the locations of start-up firms and the location of colleges and universities. His qualitative conclusions are quite similar to those of Florax (1992), namely that proximity to a college or university is not a significant factor in explaining regional variations in the incidence and location of new start-up companies. Our own work (Anderson, *et al*, 2004) questions these conclusions, at least for Sweden.

During the last two decades, data on patents have been relied upon increasingly in investigating the production of knowledge (See Griliches, 1984). In his 1990 survey paper, Griliches evaluates patent statistics as economic indicators, emphasizing that a patent represents "a minimal quantum of invention that has passed both the scrutiny of the patent office as to its novelty and the test of the investment of effort and resources by the inventor (p 1669)." He emphasizes that patents comprise only a subset of all inventions, since a great many valuable inventions are not patented, while, Trajtenberg (1990) and Jaffe and Trajtenberg (2000) caution that citation-weighted patent counts are a better measure of the value of patents than unweighted counts of patents.

Using patent counts, Acs, *et al* (2002) found that both university research and private R&D exerted substantial effects on innovative activity in US metropolitan areas, with a clear dominance of private R&D over university research. Fischer and Varga (2003) also analyzed patent counts as proxies for the output of regional knowledge production, while university research and corporate R&D investment represent the input side. They used spatial econometric methods to test for spatial effects --spillovers-- in Austria on a rather fine spatial scale, more than ninety small political districts. They confirmed the presence of local geographic spillovers, but they also found that these spillovers attenuate quickly with distance.

Jaffe (1986) investigated the link between patents and the R&D activities of firms. His research suggests that knowledge transfers occur more easily among companies in regions with a high output of patents. Companies performing research in areas where a considerable amount of research is carried out by *other* companies also appear to generate more patents per dollar spent on R&D than companies located in areas where relatively little research is carried out by *other* companies. Thus, clusters of research companies facilitate the diffusion of new knowledge. Jaffe (1989) analyzed time series data on corporate patents for US states, corporate R&D, and university research, investigating spillovers from academic research. He found a significant effect of university research on corporate patents. His research also suggested that university research may have an indirect effect on local innovation by inducing R&D spending by private firms.[2]

The research reported in this paper is perhaps closest to work currently underway by Jerry Carlino and his associates (2004) at the Federal Reserve Bank of Philadelphia. Carlino *et al* relate patent intensity (i.e. patents per capita) in U.S. metropolitan areas (MSAs) to a variety of aggregate characteristics -- size, density and specialization. Their model is based upon a cross section of 280 metropolitan areas, observing initial metropolitan conditions in 1990 and patent activity aggregated over the subsequent decade. As noted below, our analysis is based on an eight year panel of Swedish labor market areas in which we observe patent activity and metropolitan characteristics. Our statistical models vary somewhat from those employed by Carlino *et al,* and our measurements of metropolitan characteristics are somewhat more elaborate.

III. Data and Hypotheses

Our principal dependent variable is based upon patents registered to the Swedish Patents and Registration Board or the European Patent Office during the period 1994-2001. Data on Swedish patent awards publicly available include the home address of the inventor(s) of record. We allocate each invention to the labor market area in which the inventor resides. [3] Figure 1 reports the number of patents and patents per capita reported in these data. During the 1994-2001 period, about 16,500 commercial patents were approved; annual patents ranged between 1,200 and 2,200 on a slightly upward trajectory. On average, patents per ten thousand of population ranged between about 1 and 1.8. Per capita patents were largest in 1997-1998.[4]

Labor market areas are defined by the Swedish Labor Ministry on the basis of commuting patterns, using methods analogous to those used to define MSAs in the United States. Most, but not all, of Sweden's 100 labor market areas contain a central city and a number of surrounding jurisdictions. Figure 2 indicates the geography of these labor market areas; they vary substantially in size and in the intensity of patent activity. The average number of patents and the average number of patents per capita is largest in the three largest metropolitan areas, Stockholm, Gothenberg, and Malmö. Almost half of Swedish patents originated in these three labor markets. There is, however, some patent activity in each of the labor market areas, including those in the far north of the country.

Figure 3 reports the distribution of patents per capita, in six categories averaged across the eight years. In the top decile of the distribution of patents by labor market area, patents averaged about 4 per ten thousand in population. In the next 15 percent of the distribution, patents averaged about 2 per ten thousand. In the bottom decide, patents averaged about 0.5 per ten thousand.

[2] Jaffe points out that he would have preferred to carry out his regional analysis on a finer spatial scale using economically more meaningful units than US states.

[3] In the case of multiple inventors, we pro-rate each invention to the labor market in which the inventors reside.

[4] In comparison, Carlino, *et al* (2004) report 2.1 patents per ten thousand for the US during 1990-1999.

Clearly, there is considerable variation in patent awards over time and across labor markets. We investigate the systematic relationship between the level of innovative activity in these regions and four broad classes of determinants: human capital; industrial structure; agglomeration; and diversity. The link between human capital and patents presents the simplest and most straightforward hypothesis. Labor forces with more highly educated workforces are more likely to have higher levels of innovative activity and creativity, hence higher patent awards. The link between industrial structure and patents is less obvious. Traditional models of industrial organization (e.g. Shumpeter, 1935) emphasized the importance of firm size and scale in fostering innovative activity. Larger, more differentiated firms may structure divisions to persue innovations and patents. More recent scholarship (e.g., Porter 1998) emphasizes the innovative potential of smaller, more nimble, less differentiated firms.

The link of innovation to agglomeration is through local externalities across firms, increasing the likelihood of adapting advances in one firm to other firms and industries in close proximity (e.g., Glaeser, *et al* 1992). The hypothesized linkage between economic diversity and innovation follows from Jane Jacob's (1961, 1969) verbal insights about economic growth and urban heterogeneity as well as more recent work quantifying the linkage between economic diversity and economic growth (e.g., Wagner and Deller, 1998).

We assembled data to investigate these broad hypotheses across time and space using these data on innovations in Swedish labor market areas. For each labor market area, we assembled annual information on the local labor force and industrial structure. Information on labor force characteristics includes the number of employees and the distribution of their educational attainments. Information on the industrial structure includes the number of employees by industry as well as the size distribution of establishments. These labor market area data are available annually from Statistics Sweden.

We also assembled information on the research capacity and R&D facilities located in each of these labor market areas.[5] Estimates of the number of full time researchers in private firms are available annually at the county level. [6] We estimated the distribution of researchers at the level of the labor market area by distributing these county totals to constituent labor markets in proportion to the number of workers with doctoral degrees in each labor market. The number of technical researchers in the public sector (mainly at universities) is also available at the level of the labor market area.

Figure 4 reports the size distribution of non-agricultural establishments in 2001. More than 450,000 establishments (out of 751,000 non-agricultural establishments in Sweden) report no employees other than the owner. Another 150,000 establishments had fewer than five workers including the owner. Despite the large number of small establishments, they employ only a small proportion of Swedish workers. More than 17 percent of non-agricultural workers were employed in establishments of 20-49 workers, and 44 percent of the non-agricultural workforce was employed in establishments of more than 50 workers.

[5] Labor market areas containing private R&D facilities operated by the twenty largest firms in Sweden were identified by telephone survey.

[6] There are 26 counties in Sweden, amalgams of one or more labor market areas.

Figure 5 presents the rank size relationship for patents. It presents a graph of the logarithm of patent production as a function of the rank of each labor market in terms of employment. The exponential increase in patents with population rank is clearly evident in the raw data.

Table 1 summarizes the descriptive data assembled for each labor market area for each year. We measure total employment and the fraction of employees working in small (fewer than 10 employees) and large establishments (with more than 100 employees). We measure the average number of establishments per employee and also the number of establishments per employee in manufacturing. We measure the proportion of total employment in each labor market area and each year who are working in the manufacturing sector and, within manufacturing, the proportion working in four large components: paper, chemicals (including pharmaceuticals), electronics, and transport.

We measure the human capital of the labor force by the proportion of employees with post secondary education and the average years of education of the labor force. We also measure the fraction of the workforce with advanced degrees, masters and doctoral degrees, as well as the fraction of workers engaged full time in R&D activities. For each labor market area, we also record the existence of a R&D facility operated by a large private company and a university R&D facility.

We measure the spatial structure of three labor markets in each year by a series of variables reflecting density, heterogeneity, and concentration. We measure the density of employment (e.g. employees per square kilometer), of establishments, of small establishments (with fewer than 10 employees), large establishments (with more than 100 employees) and research workers in each labor market area in each year. We also compute these same density measures for the most dense political jurisdiction within each labor market area.

We measure the diversity of employment in each labor market by the Hirfindahl Index of concentration for 24 business sectors, and similarly for 14 components of the manufacturing sector. We also compute the concentration of national industry in each labor market area separately for the paper, chemical (including pharmaceuticals), electronics (including power and electricity), and transport sectors. For each labor market, we compute the share of employment in each industry relative to the share of total employment in that labor market.

Table 2 reports the mean values of these variables separately for six groups of labor market areas in 2000. These six categories correspond to the percentiles reported in Figure 3 -- that is, the 10^{th}, 25^{th}, 50^{th}, and 75^{th} and 90^{th} percentiles of the distribution of patents by labor market area during 1994-2001. The number of patents in 2000 averaged about 0.6 in each of the labor markets in the bottom decile in 2000, and it averaged 112.6 in each of the labor markets in the top decile.

There is a generally increasing share of employment in manufacturing in those labor market areas with more patent activity, and increasing shares of employment in paper, chemicals, and electronics, at least at the highest decile. The fraction of workers with post secondary schooling is generally higher in labor market areas with more patent activity. Patent activity is increasing monotonically with the fraction of workers with masters' degrees, doctoral degrees, and with the fraction of employees working in research jobs.

There is a monotonic relationship between the density of employees and the density of establishments in labor market area and the incidence of patent activity. Likewise, there is a monotonic relationship between the density of employees and establishments in the densest political jurisdiction of a labor market area and patent production.

There is no simple relationship between the measures of diversity and establishments per worker and patent activity.

IV. Statistical Models

Of course, many of the measures reported in Table 2 are themselves highly correlated, and a simple univariate comparison may be highly misleading. We can relate patent counts, η_{it}, by labor market i and year, t, to these factors by estimating a count model.

$$(1)\ \operatorname{prob}\left(\eta_{\mathrm{it}} = \mathrm{y}_{it}\right) = \frac{e^{\mu_{it}\lambda_{it}}\left(\mu_{it}\lambda_{it}\right)^{\mathrm{y}_{it}}}{\mathrm{y}_{it}!}$$

$$(2)\ \log \lambda_{it} + \log \mu_{it} = X\beta,$$

where the probability that the count η_{it} is equal to y_{it} is expressed in equation (1). The vector X represents characteristics of labor market i at time t, and β is a vector of parameters. If $\mu_{it} = 1$, the mean and the variance of the count distribution are equal, and equation (1) is a straightforward poisson model. If the mean and variance of the count distribution are unequal, parameters of the model may be represented as a straightforward negative binomial count model.[7]

Table 3 reports the coefficients of the count model, estimated by maximum likelihood methods. Since α, the overdispersion parameter, is significantly different from zero, the preferred model is the negative binomial. Model 1, the "Base Model," includes total employment and employment density, as well as measures of heterogeneity of employment, the education of the workforce, the distribution of employment by industry and the concentration of national industry in each labor market area.

The aggregate employment of each labor market area is clearly important in affecting patents. Patent activity is greater in regions where there is more economic activity. Creativity, at least as measured by patents, is larger where a larger fraction of the workforce has completed post secondary education. Patents are also larger in regions where a larger fraction of the workforce is employed in research jobs.

Model 2 experiments by considering both measures of workforce diversity. Creativity is clearly larger where there is a greater diversity of employment within manufacturing. Patent activity is also less when a larger fraction of the workforce is employed in very small firms (fewer than 10

[7] This follows, for example, if it is assumed that μ_{it} follows a gamma distribution, $\mu_{it} \sim Gamma(1/\alpha, \alpha)$. If α=0, the model is poisson. If $\alpha > 0$, the model is negative binomial.

employees) or in very large establishments (over 100 employees).

Model 3 uses the average years of education of the workforce as the measure of human capital. Model 4 disaggregates the human capital measures into the fraction with a masters degree and the fraction with doctoral degrees. These models are indistinguishable from the other measures of human capital.

Table 4 explores the relationship between the spatial structure of these labor market areas and their patent intensity. The first two models report the results of different models relating the density of employment to patent output. Ceteris paribus, it is clear that labor market areas that are denser -- in terms of employees per square kilometer -- have higher outputs of patents. Holding density constant, however, it also seems clear (from models 1 and 2) that patent output is larger in labor market areas that are more uniform in the density of employees. From Model 3, it is also clear that, holding average density itself constant, the density of very large establishments is negatively related to patent output. When the existence of private sector or university R&D facilities is accounted for, the importance of density is reduced, but certainly not eliminated.

The last three models in Table 4 report analogous results when density is measured by establishments per square kilometer. Patent output is higher when the density of establishments is higher. Holding establishment density constant, patent activity is higher when that density is more uniformly distributed within the labor market area.

In all the results reported in Tables 3 and 4, patent activity in a labor market area is greater when a larger share of national employment in chemicals, electronics, or transport is concentrated in that labor market area; patent activity is less in labor market areas containing a large fraction of national employment in pulp and paper. It is also true, consistently, that patent activity is greater when the share of aggregate employment in the local labor market area in these manufacturing sectors is smaller.

Table 5 explores the links between spatial factors and creativity for three specific fields -- medical patents (1,196 during 1994-2001), mechanical (1,869) and information technology (1,273). The table reports the results of our preferred specification in predicting patent counts in these industries and scientific specialties for the panel of labor markets during the 1994-2001 period. With no exceptions, creativity in medical and mechanical advances follows the pattern reported in Tables 3 and 4 for all innovations. For the IT sector, however, the results are quite different. Patent counts in IT are unrelated to the employment base of the labor market area; they vary with the density of the largest community, not the labor market area as a whole. Patent activity in IT also varies positively with the density of large establishments. The findings from the IT sector are worthy of further exploration.

Finally, it is possible that our statistical results are affected by the dominance of the Stockholm labor market area. As in other smaller countries, the capital region has a disproportionate share of population and economic activity. To test the robustness of our results, we have re-estimated our preferred models eliminating the Stockholm labor market area from the panel. We also re-estimated the negative binomial count model including a fixed effect for the Stockholm region. None of the principal empirical results are affected by these modifications.

Appendix Table A1 reports these models.

V. Conclusion

This paper presents an economic model to explain the spatial distribution of creativity as measured by commercial patents obtained for new knowledge created during the 1994-2001 period. Our model investigates the importance of agglomeration and spatial factors in affecting patent activity. We find that patents are responsive to the spatial distribution of workers at different levels of education and the distribution of private and university R&D facilities.

We also find, however, that the level of innovation is sensitive to the density of economic activity of differing kinds, including the density of employment and the density of large and small establishments. Our quantitative results suggest that density and urbanization really *matter* in the creation of new knowledge. For example, the level of innovation in each region can be estimated under the counterfactual of no increases in urbanization in Sweden during 1994-2001. To do this, we assume that average employment change in Sweden during 1994-2001 is applied proportionately to all the labor markets instead of the actual urbanization process that has further concentrated economic activity in larger denser regions. Using the coefficients in Table A1, we estimate that the net effect of this spatial rearrangement of employment would have a decreased patent activity by 1.9 percent per year or by about 15 percent over the period.

This is a substantial change in aggregate innovative activity. We have also found results which broadly support Jane Jacobs' hypothesis that diversity "matters" for creativity, especially within manufacturing industries. Innovation may be the mechanism responsible for the linkage between economic growth and diversity reported for U.S. cities (Glaeser, *et al*, 1992). We also find support for the importance of concentration within the electronics (power and generating) industry and the transport sector as suggested by Henderson, *et al* (1996) for U.S. capital goods industries.

Finally, our results confirm the well-known importance of human capital for the innovation creativity. Thus the presence of university research increases the number of patents awarded in a labor market by [exp (.39)-1] or by about 0.5 percent in any year, and the presence of R&D facilities established by the private sector increases the number of patents by about 0.3 percent.

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Figure 1. Aggregate patents and patents per capita, 1994-2001.

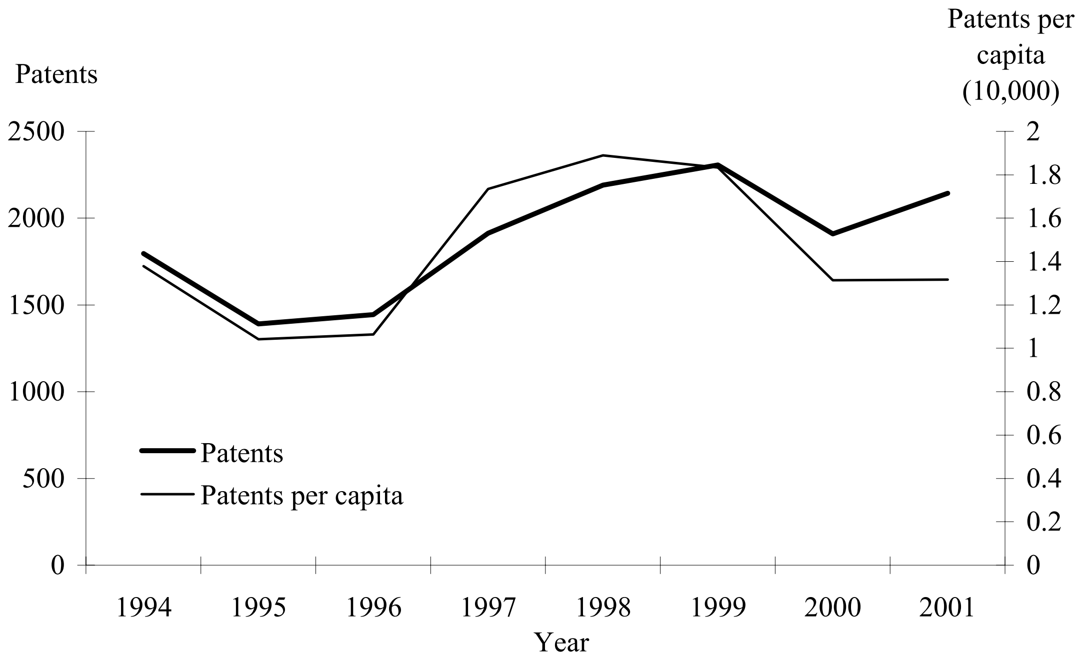

Figure 2.

Aggregate Patents
1994-2001

Patents per capita
(10,000)
1994-2001

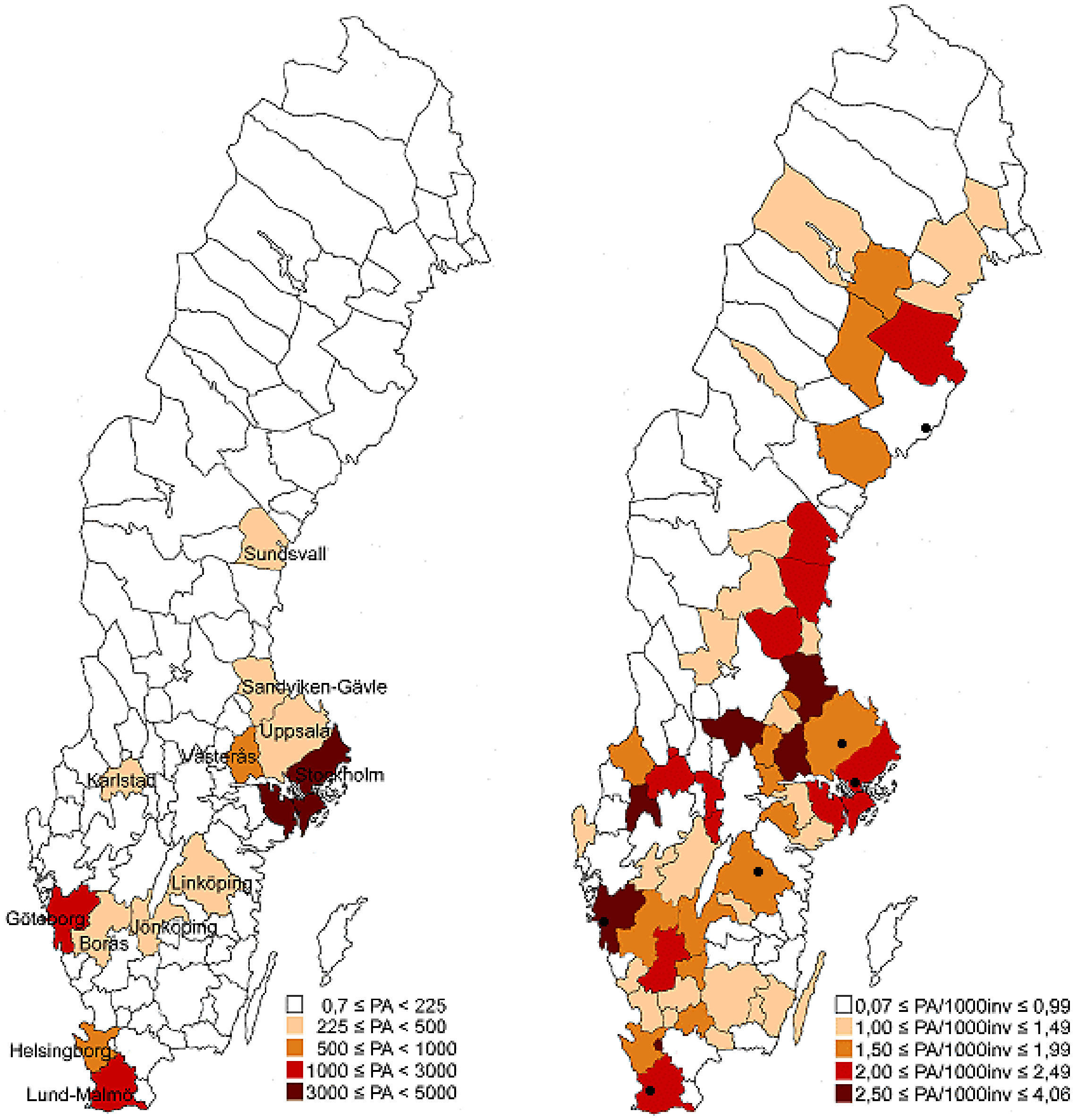

Figure 3. Average patents per capita in six different classes.

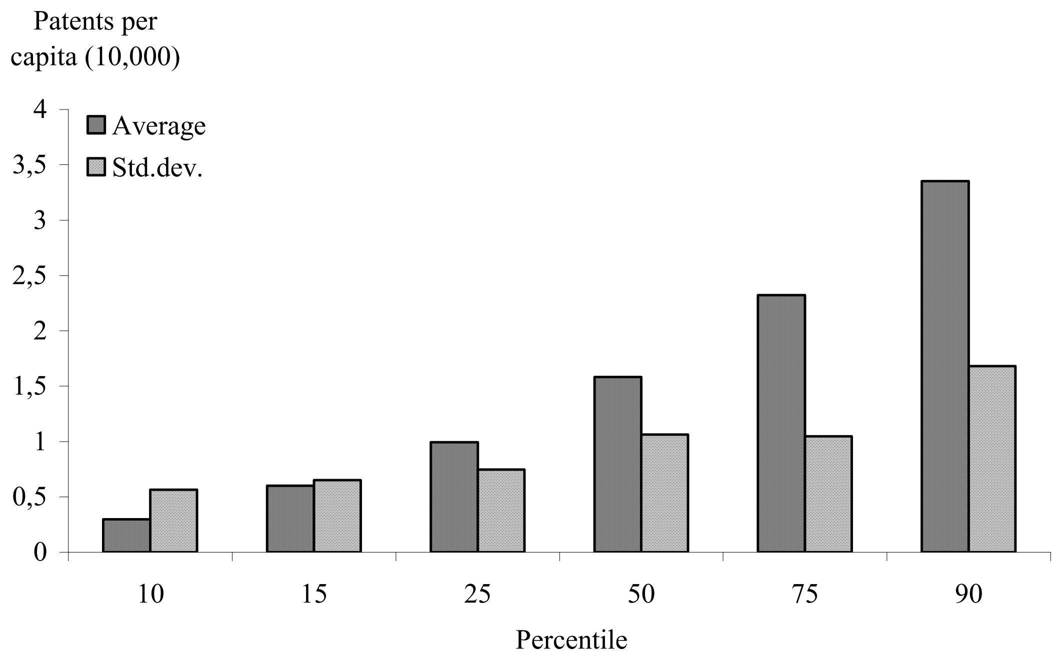

Figure 4. Number of establishments and employment by size of establishment, 2001.

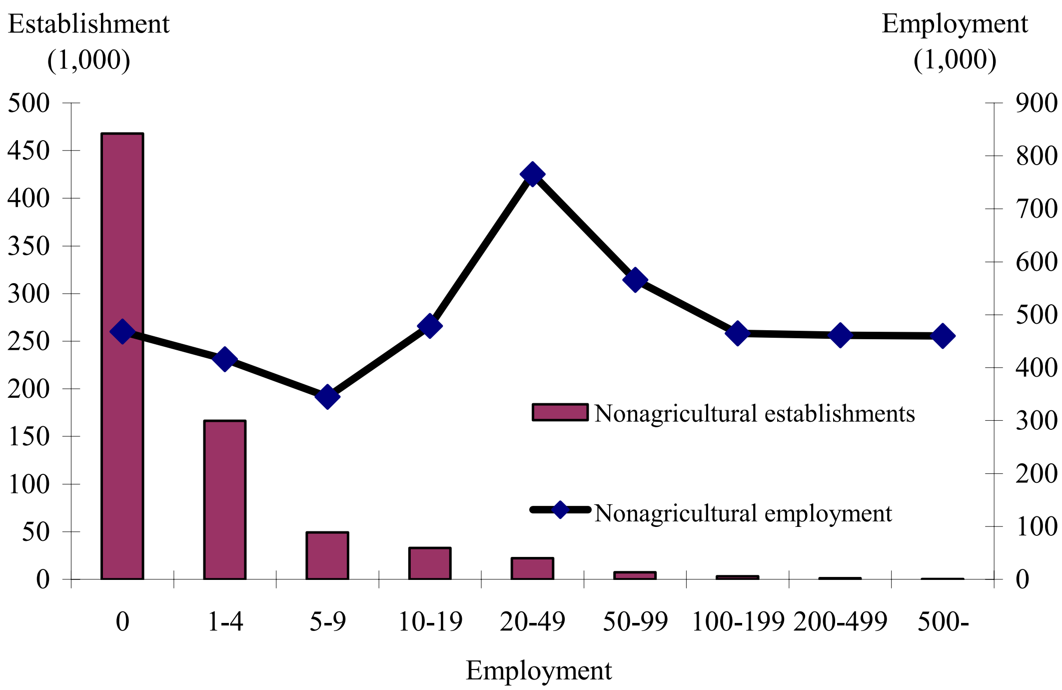

Figure 5. Total number of patents by rank of labor market size, 1994-2001.

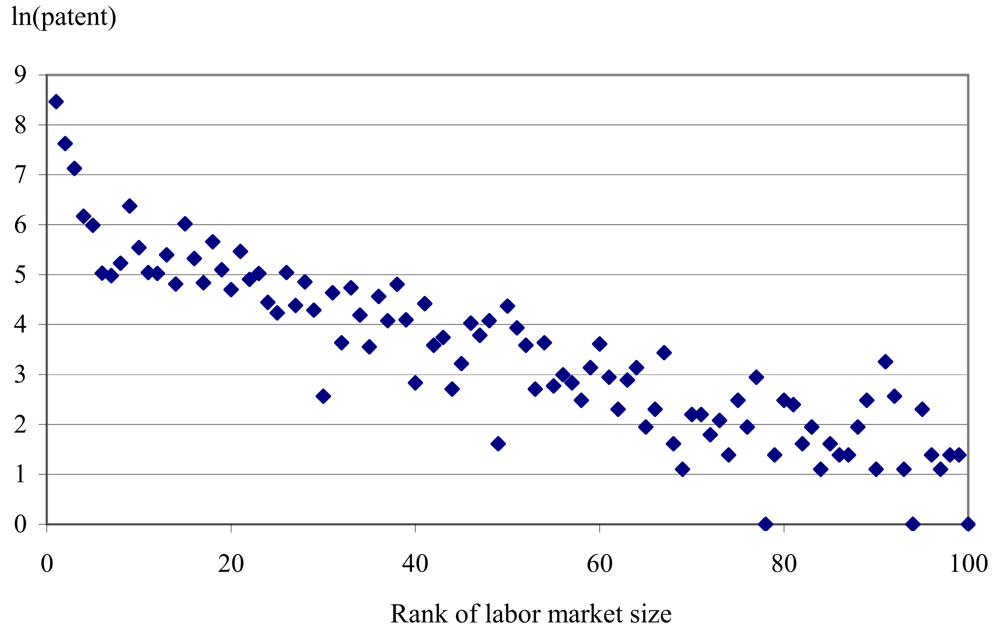

Table 1 Definitions of variables, means and standard deviations for 100 labor market areas, 1994-2001

Variable	Description	Mean	Std.dev.
Patent	Number of patents awarded	18.869	67.299
Medical Patents	Number of medical patents awarded	1.495	7.734
Mechanical Patents	Number of mechanical patents awarded	2.336	8.475
IT Patents	Number of Information Technology patents awarded	1.591	11.974
Emp	Total employment (0000)	3.861	10.866
Emp10	Proportion of employees working in establishments with less than 10 employees	0.331	0.081
Emp100	Proportion of employees working in establishments with more than 100 employees	0.263	0.102
Estab	Number of establishments	7585.369	20260.330
Estab-emp	Number of establishments per employee within the manufacturing industry	0.079	0.051
Higher ed	Proportion of employees with post graduate education	0.065	0.024
Years ed	Average number of years in education	10.731	0.323
Researchers	Proportion of employees working with R&D including those in private firms and technical researchers within higher education	0.004	0.001
R&D private	R&D facility owned by one of the 20 largest companies in the labor market area (1=yes)	0.31	0.463
R&D university	University research in labor market area (1=yes)	0.244	0.43
Density-emp	Employment per square kilometer of area in the labor market area	11.029	13.594
Density-max 1	Highest employment density of any political jurisdiction in the labor market area	61.281	306.644
Density-max 2	Highest employment density relative to average density	2.3121	4.743
Density-establ	Number of establishments per square kilometer in the labor market area	2.197	2.597
Density-max 3	Highest establishment density of any political jurisdiction in the labor market area	9.15	44.223
Density-max 4	Highest establishment density relative to average density	1.864	3.650
Density-small estab	Number of establishments with fewer than 10 employees per square kilometer in the labor market area	1.404	1.670
Density-large estab	Number of establishments with more than 100 employees per square kilometer in the labor market area	0.001	0.002
Diversity-1	Hirfindalh-index for 24 business sectors	0.117	0.022
Diversity-2	Hirfindalh-index for 14 manufacturing sectors	0.225	0.123
Share-Paper	Proportion of manufacturing employees working in the pulp and paper industry	0.117	0.112
Share-Chemical	Proportion of manufacturing employees working in the chemical industry	0.025	0.066
Share-Electronics	Proportion of manufacturing employees working in the electronic industry	0.090	0.103
Share-Transport	Proportion of manufacturing employees working in the transport industry	0.069	0.085
Con-Paper	Concentration, pulp and paper industry*	0.963	1.515
Con-Chemical	Concentration, chemical industry*	0.809	3.475
Con-Electronics	Concentration, electronic industry*	0.862	1.071
Con-Transport	Concentration, transport industry*	1.001	1.494

*Labor market's share of employment in the industry divided by its share of total employment.

Table 2
Characteristics of Labor Market Areas
by Percentile in the Number of Patents Awarded, 2000

	Percentile in Patent Awards					
Variable	10	15	25	50	75	90
Number of Patents Awarded	6	17	154	227	380	1126
Medical Patents	1	0	7	9	27	130
Mechanical Patents	0	2	17	24	37	108
IT Patents	0	1	5	3	43	161
A. Industrial composition						
Share-Paper	0.092	0.142	0.111	0.089	0.099	0.157
Share-Chemical	0.013	0.010	0.018	0.024	0.029	0.070
Share-Electronics	0.113	0.113	0.089	0.088	0.093	0.182
Share-Transport	0.069	0.024	0.084	0.104	0.055	0.060
B. Human capital						
Higher Ed	0.067	0.073	0.087	0.079	0.087	0.105
Doctors	0.001	0.001	0.002	0.002	0.003	0.004
Masters	0.066	0.072	0.085	0.077	0.085	0.101
Years Ed	10.769	10.879	11.004	10.949	11.022	11.192
Researchers	0.002	0.002	0.003	0.004	0.005	0.010
Private R&D facilities	0.100	0.067	0.200	0.360	0.533	0.700
R&D facility	0.062	0.083	0.310	0.270	0.200	0.500
C. Agglomeration						
Density-emp	4.11	3.12	10.21	11.04	15.32	28.39
Density-max-1	5.59	4.06	19.44	22.78	87.22	406.60
Density-establ	1.33	0.91	2.36	2.54	3.35	5.64
Density-max-3	1.47	0.99	3.64	4.00	13.85	64.36
Con-Paper	1.457	0.354	1.999	0.870	0.648	0.589
Con-Chemical	0.206	0.159	0.478	0.675	0.919	3.156
Con-Electronics	0.861	0.909	0.832	0.919	0.918	1.955
Con-Transport	0.757	0.352	1.049	1.558	0.972	0.682
Diversity-1	0.125	0.118	0.114	0.108	0.118	0.121
Diversity-2	0.272	0.243	0.199	0.204	0.218	0.247
D. Scope						
Establ	22629	35558	165980	155948	162852	352088
Emp	72525	111535	714081	666674	729982	1757073
Emp10	0.39	0.43	0.36	0.35	0.32	0.29
Emp100	0.19	0.17	0.24	0.25	0.28	0.32
Establ-emp	0.11	0.14	0.08	0.08	0.07	0.06

Table 3
Negative Binomial Estimates of Patent Counts

	Base Model		**Size and Diversity**		**Human Capital and R&D**			
	Coefficient	t-ratio	Coefficient	t-ratio	Coefficient	t-ratio	Coefficient	t-ratio
Density-emp	0.0345	6.71	0.0209	5.08	0.0221	5.90	0.0237	7.54
Diversity-1	-13.9704	-6.04	0.9631	0.30	1.8591	0.62	0.6525	0.23
Diversity-2			-5.2550	-8.94	-5.3506	-9.77	-4.8275	-9.37
Emp	0.0177	2.92	0.0216	4.74	0.0254	6.27	0.0270	7.37
Emp10			-5.6338	-3.97	-6.0755	-4.53	-2.5996	-1.91
Emp100			-1.1871	-1.22	-2.3414	-2.55	-0.8980	-1.00
Estab-emp			-12.6241	-6.72	-14.6312	-8.00	-14.7433	-8.38
Higher Ed	26.4301	8.84	18.4055	7.14				
Years ed					1.7897	12.19	1.3954	9.60
R&D private							0.2228	2.82
R&D university							0.6207	7.23
Researcher	39.4842	3.39	43.3043	4.21	30.8369	3.41		
Share-Paper	1.5701	4.19	0.2740	0.84	-0.0228	-0.08	-0.4887	-1.68
Share-Chemical	-2.7703	-1.45	-2.2210	-1.32	-3.3990	-2.08	-1.8304	-1.15
Share-Electronics	-7.3179	-6.08	-3.3947	-2.82	-4.4146	-3.89	-4.7445	-4.39
Share-Transport	-2.9132	-2.08	-3.9906	-3.23	-4.1279	-3.60	-4.3396	-4.15
Con-Paper	-0.1199	-3.66	-0.1545	-5.26	-0.1411	-5.06	-0.1387	-5.22
Con-Chemical	0.0466	1.31	0.0273	0.87	0.0545	1.80	0.0231	0.79
Con-Electronics	0.6809	6.15	0.2857	2.65	0.3884	3.80	0.4312	4.40
Con-Transport	0.1485	1.85	0.1536	2.25	0.1495	2.34	0.1589	2.70
alpha	0.7678	14.73	0.5026	13.22	0.4110	12.44	0.3490	11.71
Log likelihood	-2303.5647		-2189.7899		-2146.6799		-2116.7233	
Pseudo R2	0.1782		0.2188		0.2342		0.2449	

Table 4
Spatial Structure and Creativity: Negative Binomial Models

	Employment Density								Establishment Density							
	Coefficient	t-ratio	Coefficient	t-ratio	Coefficient	t-ratio	Coefficient	t-ratio	Coefficient	t-ratio	Coefficient	t-ratio	Coefficient	t-ratio	Coefficient	t-ratio
Density-emp	0.0246	6.82	0.0182	4.73	0.0322	3.54	0.0208	2.38								
Density-max 1	-0.0032	-7.75			-0.0032	-7.90	-0.0025	-6.31								
Density-max 2			-0.0659	-3.23												
Density-establ									0.1392	6.89	0.0877	4.03	0.2222	2.57	0.1586	1.98
Density-max 3									-0.0210	-7.56			-0.0219	-7.88	-0.0165	-6.17
Density-max 4											-0.1132	-3.86				
Density-small establ					0.0341	0.65	0.0750	1.49					-0.0217	-0.21	0.0261	0.27
Density-large establ					-114.4761	-2.76	-70.6688	-1.68					-120.4238	-3.11	-81.9333	-2.10
Diversity-1	1.3535	0.48	1.0211	0.34	1.7612	0.62	1.0986	0.40	1.2310	0.43	1.1577	0.39	1.5095	0.53	0.9908	0.36
Diversity-2	-4.4732	-8.42	-5.0670	-9.24	-4.0973	-7.55	-4.1972	-8.17	-4.4574	-8.33	-5.0593	-9.26	-4.0575	-7.46	-4.1658	-8.14
Emp	0.1227	9.59	0.0573	5.41	0.1258	9.92	0.1047	8.44	0.1179	9.17	0.0693	5.84	0.1243	9.48	0.1010	7.97
Emp10	-5.0905	-3.91	-6.2463	-4.69	-5.0737	-3.65	-3.0150	-2.17	-5.9030	-4.51	-7.1281	-5.34	-5.9322	-4.43	-3.4686	-2.57
Emp100	-2.2879	-2.60	-2.4826	-2.72	-1.5884	-1.73	-0.7553	-0.83	-2.4094	-2.73	-2.6626	-2.92	-1.6848	-1.86	-0.7784	-0.87
Estebl-emp	-13.8102	-7.84	-14.7110	-8.10	-13.4590	-7.53	-13.6663	-7.84	-13.6007	-7.66	-14.6069	-7.97	-13.3680	-7.42	-13.6756	-7.80
Years ed	1.7015	11.84	1.8438	12.54	1.6404	11.0	1.3161	8.87	1.7109	11.91	1.8026	12.24	1.6626	11.01	1.3229	8.90
Researchers	18.3841	2.04	26.6607	2.90	16.5365	1.84			16.1962	1.82	26.9238	2.94	14.1516	1.57		
R&D private							0.2548	3.29							0.2462	3.16
R&D university							0.3949	4.21							0.4114	4.47
Share-Paper	-0.2034	-0.70	-0.1448	-0.48	-0.1420	-0.49	-0.3489	-1.23	-0.1638	-0.56	-0.1169	-0.39	-0.1125	-0.39	-0.3324	-1.18
Share-Chemical	-3.2012	-2.00	-3.4334	-2.12	-2.9053	-1.83	-2.3104	-1.47	-3.6682	-2.27	-3.6718	-2.25	-3.4594	-2.15	-2.6154	-1.65
Share-Electronics	-3.8678	-3.59	-3.6930	-3.25	-3.5524	-3.30	-3.7557	-3.58	-3.7380	-3.44	-3.4681	-3.05	-3.3933	-3.14	-3.7022	-3.53
Share-Transport	-5.6021	-5.03	-4.3388	-3.83	-5.4536	-4.94	-5.4293	-5.26	-5.3345	-4.78	-4.3405	-3.82	-5.1937	-4.65	-5.3073	-5.13
Con-Paper	-0.1383	-5.12	-0.1411	-5.12	-0.1249	-4.70	-0.1262	-4.80	-0.1410	-5.19	-0.1397	-5.09	-0.1255	-4.76	-0.1258	-4.85
Con-Chemical	0.0514	1.74	0.0566	1.88	0.0534	1.82	0.0370	1.28	0.0650	2.18	0.0659	2.18	0.0715	2.39	0.0487	1.66
Con-Electronics	0.3482	3.61	0.3257	3.19	0.3281	3.42	0.3452	3.65	0.3402	3.50	0.3065	3.01	0.3166	3.28	0.3418	3.61
Con-Transport	0.2207	3.57	0.1569	2.49	0.2282	3.72	0.2191	3.79	0.2113	3.41	0.1575	2.50	0.2216	3.60	0.2189	3.79
alpha	0.3625	12.11	0.4007	12.34	0.3520	11.95	0.3141	11.31	0.3645	12.12	0.3977	12.31	0.3521	11.92	0.3120	11.26
Log likelihood	-2116.5042		-2141.5733		-2112.2064		-2096.0972		-2118.0405		-2140.2873		-2113.1707		-2095.5383	
Pseudo R2	0.2450		0.2360		0.2465		**0.2523**		0.2444		0.2365		0.2462		**0.2525**	

Table 5
Spatial Structure and Creativity:
Results from Medical, Mechanical and Information Technology Sectors

Variable	Medical				Mechanical				Infromation Technology			
	Coefficient	t-ratio	Coefficient	t-ratio	Coefficient	t-ratio	Coefficient	t-ratio	Coefficient	t-ratio	Coefficient	t-ratio
Density-emp	0.0365	2.45	0.0248	1.79	0.0337	2.51	0.0326	2.42	-0.0271	-1.28	-0.0148	-0.67
Density-max 1	-0.0003	-0.44	-0.0001	-0.11	-0.0025	-4.83	-0.0025	-4.82	0.0016	2.44	0.0007	0.99
Density-small establ	0.1186	1.61	0.1648	2.40	0.0057	0.07	0.0103	0.13	0.0063	0.06	0.0341	0.29
Density-large establ	-134.4654	-1.46	-10.0535	-0.11	-33.8936	-0.48	-16.2761	-0.22	429.3207	3.26	412.6678	2.95
Diversity-1	-4.7481	-0.51	-12.1521	-1.25	-20.7297	-3.44	-21.1944	-3.51	1.6205	0.10	-3.2519	-0.19
Diversity-2	-7.2210	-3.64	-3.0848	-1.73	-5.4854	-4.74	-5.2178	-4.65	-15.4424	-4.29	-10.5093	-3.03
Emp	0.0317	1.67	0.0250	1.57	0.1044	6.17	0.1038	6.15	-0.0187	-0.83	0.0076	0.31
Emp10	-1.2015	-0.29	0.5543	0.12	-7.9244	-2.90	-7.6501	-2.65	-14.3607	-2.04	-21.9190	-2.64
Emp100	2.6153	0.91	2.1100	0.72	-2.7950	-1.52	-2.7874	-1.47	-11.9661	-2.75	-14.2556	-2.99
Estab-emp	-7.4542	-1.25	-5.4318	-0.92	-20.2433	-4.42	-20.3949	-4.42	-29.3391	-2.50	-22.6575	-1.82
Years ed	0.8212	2.28	0.4691	1.30	1.5332	6.00	1.5153	5.70	4.5198	8.56	5.1511	9.09
Researchers	47.7384	3.14			9.5932	0.74			75.4578	4.08		
R&D private			-0.0250	-0.13			0.0085	0.06			0.0216	0.07
R&D university			1.3481	5.85			0.1278	0.81			0.4345	1.24
Share-Paper	0.0316	0.46	-0.2600	-0.29	-0.4522	-6.32	-1.5522	-2.92	-0.3579	-1.93	3.4969	2.29
Share-Chemical	0.0005	0.01	6.5208	1.51	0.0463	0.73	-3.4314	-1.02	0.5007	3.55	-23.9139	-3.05
Share-Electronics	-0.0032	-0.01	-4.3522	-1.25	-0.1872	-0.86	-0.8328	-0.36	0.2991	0.55	-4.7188	-0.87
Share-Transport	-0.0137	-0.07	2.8021	1.02	0.3653	3.26	-8.3187	-4.12	0.2858	0.96	-3.8458	-0.88
Con-Paper	1.1387	1.28	0.0497	0.73	-1.4375	-2.72	-0.4599	-6.37	5.2976	3.62	-0.2117	-1.14
Con-Chemical	-1.2841	-0.29	-0.1123	-1.19	-3.7765	-1.15	0.0389	0.61	-27.0490	-3.80	0.4394	2.90
Con-Electronics	-1.3991	-0.40	0.3818	1.16	-0.6994	-0.30	-0.1605	-0.74	-4.9661	-0.89	0.5222	1.01
Con-Transport	0.5083	0.17	-0.1260	-0.73	-8.6204	-4.11	0.3474	3.21	-6.8843	-1.52	0.1787	0.65
alpha	0.1696	1.76	0.1304	1.80	0.4132	5.96	0.4068	5.89	0.2399	2.37	0.3654	2.64
Log likelihood	-510.1798		-496.9562		-941.8354		-941.7118		-354.0849		-360.8943	
Pseudo R2	0.3606		0.3772		0.2929		0.2930		0.4131		0.4018	

Appendix Table A1
Sensitivity of Results to the Treatment of Stockholm

Variable	Fixed Stockholm effect				Without Stockholm			
	Coefficient	t-ratio	Coefficient	t-ratio	Coefficient	t-ratio	Coefficient	t-ratio
Density-emp	0.0203	2.08	0.0099	1.04	0.0178	1.76	0.0074	0.74
Density-max 1	-0.0028	-6.28	-0.0021	-4.81	-0.0028	-6.12	-0.0021	-4.69
Density-small establ	0.0167	0.32	0.0648	1.28	0.0290	0.53	0.0786	1.48
Density-large establ	-99.2655	-2.40	-60.43	-1.44	-102.6904	-2.47	-64.7450	-1.53
Diversity-1	-0.0707	-0.02	-0.04	-0.01	-0.0889	-0.03	0.0453	0.02
Diversity-2	-3.7415	-6.83	-4.04	-7.86	-3.6697	-6.65	-3.9974	-7.74
Emp	0.1582	9.41	-0.13	8.13	0.1637	9.50	0.1337	8.19
Emp10	-5.2018	-3.76	-3.22	-2.33	-5.2724	-3.77	-3.3159	-2.37
Emp100	-1.5579	-1.72	-0.80	-0.89	-1.5304	-1.68	-0.7798	-0.86
Estebl-emp	-13.5016	-7.60	-13.77	-7.92	-13.3771	-7.49	-13.6424	-7.81
Years ed	1.6388	11.05	1.29	8.72	1.6395	10.96	1.2854	8.60
Researchers	6.6915	0.71			5.0270	0.53		
R&D private			0.25	3.30			0.2554	3.30
R&D university			0.35	3.74			0.3408	3.56
Share-Paper	-0.2082	-0.73	-0.33	-1.18	-0.2189	-0.76	-0.3235	-1.15
Share-Chemical	-2.7934	-1.78	-2.25	-1.45	-2.7645	-1.76	-2.2566	-1.44
Share-Electronics	-3.2537	-3.03	-3.53	-3.38	-3.2541	-3.01	-3.5286	-3.34
Share-Transport	-5.2736	-4.80	-5.48	-5.33	-5.2522	-4.74	-5.4926	-5.30
Con-Paper	-0.1169	-4.49	-0.12	-4.55	-0.1158	-4.44	-0.1163	-4.49
Con-Chemical	0.0567	1.96	-0.41	1.45	0.0573	1.97	0.0425	1.48
Con-Transport	0.3074	3.21	0.3251	3.44	0.3094	3.21	0.3253	3.41
Con-Transport	0.2221	3.65	0.2244	3.9	0.2226	3.63	0.2266	3.91
alpha	0.3432	11.86	0.3083	11.25	0.3495	11.80	0.3154	11.22
Log likelihood	-2107.5586		-2092.584		-2051.5539		-2037.2587	
Pseudo R2	0.2482		0.2535		0.2250		0.2304	