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Scientific capabilities and technological performance of national innovation systems: An exploration of emerging industrial relevant research domains

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Today's theories and models on innovation stress the importance of scientific capabilities and science-technology proximity, especially in new emerging fields of economic activity. In this contribution we examine the relationship between national scientific capabilities, the science intensity of technology and technological performance within six emergent industrial fields. Our findings reveal that national technological performance is positively associated with scientific capabilities. Countries performing better on a technological level are characterized both by larger numbers of publications and by numbers of involved institutions that exceed average expected values. The latter observation holds for both companies and knowledge generating institutes actively involved in scientific activities. As such, our findings seem to suggest beneficial effects of scientific capabilities shouldered by a multitude of organizations. In addition, higher numbers of patent activity coincide with higher levels of science intensity pointing out the relevance of science 'proximity' when developing technology in newer, emerging fields. Limitations and directions for further research are discussed.

Introduction

Innovation is one of the major drivers behind economical development and as a consequence a primary concern for practitioners, policy makers and researchers alike. In today's theories and models on innovation, the contribution of knowledge is cast in a central role, implying an increased interest in the part that knowledge generating institutes (KGIs) – such as universities and public research centres – can play in today's innovation systems. Combining this with the obvious role of business actors and the important function of governments in stimulating and regulating innovation, a multiple-actor perspective emerges in which interactions figure prominently. Innovation scholars

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have captured this multitude of actors and interactions in a strand of theories and models that increasingly move away from linear assumptions. Network dynamics, interactions and circularity have become core elements in today's innovation studies, as can be witnessed in the work on scientific networks (PAVITT, 1997; STEINMULLER, 1994; DAVID et al., 1997); the 'Triple Helix' model of industry, academia and government interactions (LEYDESDORFF & ETZKOWITZ, 1996; ETZKOWITZ & LEYDESDORFF, 1998) and the concept of national or regional 'innovation system' (NELSON, 1993; OECD, 1999). Theories and models on regional clustering and innovation networks further illustrate how cooperation and interaction are recognized as important ingredients for the development of the innovative potential of regions or nations (PORTER, 1995; VARGA, 1998).

Several authors have empirically confirmed the role of scientific centres for *regional* development. ANSELIN et al. (1997) provided evidence of local spillovers at the US state and MSA (Metropolitan Statistical Area) level. BLIND & GRUPP (1999) examined eighteen technology zones in Baden-Würtemberg and Nordrhein-Westfalen, and established a clear link between the presence of public institutions of higher learning and the technology-output in a particular geographical area. More recently, FISCHER & VARGA (2003) empirically established the importance of geographically mediated knowledge spillovers from university research activities to regional knowledge production in high-technology industries in Austria. They showed geographically mediated university spillovers to transcend the spatial scale of political districts and demonstrated a clear distance decay pattern for such spillovers. NIOSI & BAS (2001), analyzing Canadian biotech clusters, found universities – along with government laboratories and a few large firms – to attract entry of new firms. MONJON & WAELBROECK (2003) found that spillovers from universities to innovative firms can provide benefits to those firms. They found a differential effect according to the type of innovation that is pursued: incremental innovations benefit most from knowledge spillovers. Highly innovative firms, working at the frontier of academic knowledge, were found to benefit more from collaborative research with foreign universities.

Likewise, the concept of innovations systems has been advanced and elaborated on the national level (e.g. FREEMAN, 1987; LUNDVALL, 1992; NELSON, 1993; PATTEL & PAVITT, 1994; PORTER, 1995). Also at this level, understanding the linkages among actors that are involved in innovation is seen as crucial for improving technological performance. Innovation and technical progress are seen as the result of a complex set of relationships among actors producing, distributing and applying various kinds of knowledge. The innovative performance of a *country* largely depends on how these actors relate to each other, as elements of a collective system revolving around knowledge creation, use of knowledge and technologies adopted.

These theoretical and conceptual evolutions, along with the empirical support, highlight the relevance of a set of indicators to allow studying and analyzing the relationship between the presence of scientific actors and capabilities on the one hand and technological performance on the other hand. Bibliometric indicators have, since a few decades, been widely adopted for benchmarking and assessing science and technology (see for instance the European Reports on Science and Technology Indicators and the US National Science Foundation Reports on Science and Engineering Indicators). Publication related indicators have served mostly in mapping scientific efforts, while patent related indicators have been applied for assessing technological activity. Increasingly, quantitative indicators are designed to depict relatedness and interdependencies between the science and technology sphere, thereby grasping more completely the concept of what has nowadays become referred to as 'innovation system' (SCHMOCH, 1997; TIJSSEN, 2001). Such indicators include public-private coauthored publications and co-owned patents; as well as citations between both activity spheres, mostly scientific references in patents (NARIN et al. 1997; OECD, 1997; VERBEEK et al., 2002; TIJSSEN et al. 2000).

At the same time, empirical studies including indicators of scientific capabilities, technological performance and their relatedness on the level of *national* innovation systems, seem scarce. VAN LOOY et al., (2003) investigated the impact of science-technology relatedness on the effectiveness of technology development on a country level. In science intensive fields, they found a positive relation between the science intensity of patents (measured by the amount of non-patent references) and technological productivity. Their findings suggest the relevance of fostering relations between knowledge generating actors and technology producers, especially in science intensive fields. In this analysis, indicators of a country's scientific capabilities were not taken into account. The observed positive relationships might therefore stem from the presence of scientific capabilities. In this case, one would merely be registering 'spill over' effects that could be assessed equally and more easily by established bibliometric indicators pertaining to scientific publications. Hence, further analysis - whereby indicators of scientific capabilities are taken into account – is required for assessing the relevancy of non-patent references to explain differences in technological performance. Our contribution is to be situated in this area. The associations between the presence of scientific capabilities and technological productivity will be explored through the following questions:

- To what extent are scientific capabilities positively related to the technological performance of nations?
- Is science-technology relatedness – as measured by the amount of non-patent references – still positively associated with technological performance when scientific capabilities are brought into the equation?

In our analysis, we focus on emerging and knowledge-intensive fields, as the potential role of scientific capabilities for the development of technological activities seems to be most outspoken within such domains. The data pertain to the following 'hot topics', i.e. emerging domains with considerable levels of industrial relevance:

- Fuel Cells
- Stem Cells
- Conductive Polymers
- Nano-electronics
- Femto-second lasers
- Tissue Engineering/Alzheimer's Disease

All indicators and concepts are aggregated on a country level, providing a picture of scientific and technological activity that corresponds to the level of 'national' innovation systems. The results obtained should hence be interpreted on this level of analysis. In the next section, we will discuss the methodology used to extract and validate the data as well as the concepts and indicators used. Equipped with this background, data sources and obtained results will be presented. We conclude by discussing the results and their implications.

Constructs & indicators

Data extraction, cleaning and validation efforts

In order to extract the relevant data for the different domains, a dual expert-driven approach was followed.[1] Based on a review of relevant technical literature of the field, a list of pertinent key words has been outlined. This list of key words was verified and – where needed – adapted by domain experts. For patent extraction, additional search criteria related to technology classes. Resulting search keys were used for extracting patents and publications. In a second phase, the obtained set of publications and patents was again verified by experts in order to assess their relevancy for the domains under study. In total, 21 experts contributed to this exercise.[2]

The validated list of relevant patents and publications served as a starting point to delineate the number of companies and knowledge generating institutes involved per country. This implied the elimination of different name formats of companies and knowledge generating institutes, an exercise based on the CWTS thesaurus of main organizations having published one or more research papers in the Thomson/ISI

[1] For a full description of the methodology applied, we refer to the forthcoming EC report by TIJSSEN et al.: *Centres of European Scientific Excellence in Industrial-Relevant Research Areas* (CESE-IRRA).
[2] Besides professors of the University of Leiden and K.U.Leuven, researchers both from Industry (e.g; Agfa Gevaert, Umicore Corporate R&D) and from Public Research Organisations (IMEC, Be; Fraunhofer, DE) were involved in this exercise. In addition, several experts of the EC (DG Research) actively contributed.

database since 1990. A similar thesaurus of patent assignee names,[3] which is being developed by K.U.Leuven, was also used. Additional manual verification and correction turned out necessary to arrive at sufficient levels of accuracy. Some specific rules, related to aggregating and allocating publications and patents to countries, guided this process. For patents, country allocation was based on the nationality(ies) of the assignee(s). For publications, the nationality(ies) of the affiliated organization(s) was used. In the case of international co-patenting or co-publications, country allocation was based on full counts. Companies filing patents for subsidiaries in different countries were considered as being situated in these different countries, if the assigneeship reflected different nationalities.[4] For knowledge generating institutions, the institutional level (university, public research organizations) was considered.[5] The resulting final list of institutions – both companies and KGIs – for each field has also been validated and adjusted where needed by experts.[6]

Scientific capabilities

The total amount of publications in a specific domain for a given country is used as an indicator of scientific performance. Relevant publications were retrieved from the Thomson Scientific's Science Citation Index[7] based on the search keys that have been developed for each of the domains. In a next step, all retrieved publications were allocated to countries, based on the 'nationality' of the authors' organizational affiliation. In the case of internationally co-authored papers, full counts were applied to acknowledge all countries involved. In addition, the number of research institutes and the number of companies to which these publications are affiliated were included as explanatory variables. Publications with a company affiliation are mostly company-university co-authored papers. As such, company-involvement in publications could also be considered as signaling science-technology interactions (TIJSSEN, 2004).

[3] This list focus is on European and American universities (see VAN LOOY et al., 2003) and Top 10 companies in all industries.

[4] E.g. GlaxoSmithKline acts as assignee with address fields relating to the US, UK and Belgium; in this case the patents are assigned to the different nations involved.

[5] So in the case different departments within one university or public research organization appears as assignee/affiliation, harmonization on the level of the institution has been applied.

[6] Validation implied the involvement of two scientific officers of the EC (DG Research) as well as experts in the field of science and technology policy studies.

[7] The data were extracted from the CWTS bibliometric database, which is based on the Thomson Scientific Citation Indices (CD ROM version) and operated by CWTS under a licence agreement with Thomson Scientific.

Technological performance

Technological performance is measured by the number of patents produced in a given country for each year in the time period 1997–2001. USPTO patents were used, as these contain significantly more NPRs than EPO patents. Both variables were logarithmically transformed to obtain a normal distribution.[8] Note that only those countries are analyzed where patenting activity is observed in the considered timeframe. Patent output is used as the dependent variable, and considered an indication of the technological performance of a given country in a given year. As such, we will examine whether and to what extent differences in scientific activities as well as in S-T relatedness coincide with differences in the amount of patent activity taking place.

Finally, two control variables were included. First of all, country size – in terms of population – was taken into account. Second, the year in which patent activity took place (application date) was introduced. This is of special importance, because granted patents were used for the time period 1997–2001. Given the time period between applying and granting patents, the data extracted in 2003 show a decreasing trend – in terms of absolute numbers – from 2000 onwards as Table 1 makes clear.

Table 1. Distribution of observations by year
(number of countries*fields for which observations are available)

	Frequency	Percent	Cumulative percent
1997	72	29.9	29.9
1998	68	28.2	58.1
1999	65	27.0	85.1
2000	30	12.4	97.5
2001	6	2.5	100.0
Total	241	100.0	

Science–technology relatedness

An additional indicator of science-technology relatedness that we introduced is the amount of non-patent references found in patents. These non-patent or ‘other’ references are included on the front page of patents; they signal the presence of (non-patent) prior art that qualifies and contextualizes the novelty, inventiveness and applicability of the patent claims. Any interpretation of non-patent references should take into account the specific context of use, i.e. the patent application and granting process (MICHEL & BETTELS, 2001; HARHOFF et al., 2003; MEYER et al., 2003; VAN LOOY et al., 2003).

[8] Such a transformation has also been applied to the scientific and S-T variables, for the same reason.

Patents are documents issued by an authorized governmental agency which grants the right exclusively to the applicant to produce or use a specific new device, apparatus or process for a limited time period. Patents are granted to the applicant after an examination that focuses on the novelty, inventive activity and industrial applicability. During the granting process, patent examiners review the prior art pertaining to the invention. While applicants are obliged – within the USPTO granting process – to provide an overview of all known relevant prior art, which can be either patents or other written documents, patent examiners do not limit themselves to the prior art signaled by inventors and/or applicants. Based on information, archives and databases available, patent examiners in the end decide which references are relevant to assess the claims made. It are the examiners references, used to decide on granting, including restricting claims, that are to be found on the front page of patent documents, besides information pertaining to the invention, assignee(s) and inventor(s). These references do not necessarily coincide with references provided by the applicant; references provided by the applicant can be omitted while examiners might add references as well.

Stated otherwise, front page references as found in patent documents are being introduced during the granting process for the purpose of evaluating the novelty and inventiveness of the claims and their applicability, including contextualizing the claims that are being made.

It is clear that the specific role of references within patent application procedures is to some extent different from the role references or citations play within scientific publications. Within articles references indicate sources of influence or serve as reference points to delineate differences (novelty). At the same time, references to previous work in scientific publications are introduced by the authors (sometimes with some support of reviewers), implying in all cases that the cited references are known to the author(s) and hence have had a certain influence on the genesis of the ideas and insights developed within the article or paper. This clearly is not necessarily the case for the front page references to be found within patent documents. References might be added by examiners without the inventors and/or applicants being aware of their presence or without this knowledge having influenced in any way the creation of the invention, as documented recently by MEYER (2000) and TIJSSEN et al. (1999).

Against this background, a citation is perceived here as a bit of information linking two different documents. The presence of scientific research in the ‘prior art’ description of a patented invention, is seen as an indicator of the ‘distance’ between scientific findings on the one hand and technology development on the other hand. As references to be found in patents are a reflection of prior art, more references towards science fields signal more relevant prior art derived from scientific sources. While this does not equal a uni-directional, influencing or contributing, link from the cited paper towards the citing patent, it is clear that the more scientific references are considered relevant for assessing and contextualizing the claims made within the patent, the closer the technology is situated to scientific activity. As such it can be noticed that some of the debate around the nature and meaning of non-patent references arises from neglecting the precise role non-patent references fulfill within the patent procedure. Rather than equaling non-patent references as signaling direct or uni-directional influences, contributing to the genesis and development of the invention at hand, they are part of the context in which the patent and its claims are to be situated. Hence, the more scientific references are to be found within patents, the more technology development is considered here as situated in the neighborhood or vicinity of scientific developments.

Indicators reflecting the amount of non-patent references can be grasped through directly available and accessible data: sources. More specifically, we use the amount of non-patent references as found within published USPTO patent documents as an indicator of the science intensity or science proximity of patents. A method towards the construction of this indicator was designed and implemented previously (see VERBEEK et al., 2002a). The designed method encompasses a complex parsing algorithm, based on a textual analysis approach that parses the references to be found in patents. Within the framework of the analysis reported here, the number of other references identified by means of this parsing algorithm is used as an indicator of the science intensity of each patent.[9]

For each domain, year and country, the total number of non-patent references (NPRs) was calculated for all the patents implied. In a next step, the average number of NPRs was calculated by domain, year and country. Averages (per patent) were used instead of absolute numbers to avoid the registration of a mere size effect: absolute number of non-patent references is very strongly related to total amount of patents ($r=0.93$, $p<0.001$).

Analysis: Descriptive statistics and correlations

Before looking at the specific analyses conducted to address the aforementioned questions, some descriptive statistics will be provided. Tables 2 and 3 provide an insight in the distribution of data by field and by country.

[9] A detailed content analysis of 10.000 other references reveals that about 60% of these references are references towards scientific journals (see CALLAERT et al., forthcoming). The remainder relates to books, company reports databases and the like. At the same time, the correlation between the number of other references and the number of journal references amounts to 0.7 ($p < 0.0001$); while at the same time variation across fields is limited (0.6–0.8), allowing to use the frequency of occurrence of other references to address the research questions outlined.

Table 2. Distribution of observations by domain/hot topic
(Number of years*countries for which observations are available)

	Frequency	Percent	Cumulative percent
Nano-electronics	61	25.3	25.3
Femto-second Lasers	55	22.8	48.1
Fuel Cells	38	15.8	63.9
Alzheimer	36	14.9	78.8
Conducting Polymers	31	12.9	91.7
Stem Cells	20	8.3	100.0
Total	241	100.0	

Table 3. Distribution of observations by country
(Number of domains*years for which observations are available)

	Frequency	Percent	Cumulative percent
JAPAN	26	10.8	10.8
USA	26	10.8	21.6
GERMANY	21	8.7	30.3
CANADA	17	7.1	37.3
FRANCE	15	6.2	43.6
SOUTH KOREA	15	6.2	49.8
UK	15	6.2	56.0
TAIWAN	13	5.4	61.4
ITALY	12	5.0	66.4
SWITZERLAND	12	5.0	71.4
ISRAEL	9	3.7	75.1
DENMARK	8	3.3	78.4
NETHERLANDS	7	2.9	81.3
AUSTRALIA	6	2.5	83.8
FINLAND	5	2.1	85.9
BELGIUM	4	1.7	87.6
HONG KONG	3	1.2	88.8
SINGAPORE	3	1.2	90.0
SWEDEN	3	1.2	91.3
ALL OTHER	21	8.7	100
Total	241	100.0	

Table 4 gives a summary overview of the different variables, broken down by domain. The reported figures relate to the observed values, averaged over the countries and years that are included in the analysis. As Table 4 makes clear, both patent and publication outputs vary by domain. With regard to patents, higher figures are observed for Femto-second Lasers, Nanoelectronics and also Fuel Cells. For publications, average figures are highest for Nano-electronics and especially for Stem Cells.

Table 4. Average of variables by domain (over year and country)

	Alzheimer	Fuel Cells	FS – Lasers	Nano-Electronics	Conductive Polymers	Stem Cells
Patents	9.97	14.53	33.51	19.90	5.87	6.45
Publications	54.33	19.45	18.98	98.28	23.10	530.70
# of publishing KGIs	18.22	8.89	8.75	26.34	12.00	96.85
# of publishing Companies	1.72	2.39	1.13	3.54	1.97	13.65
Average amount of Non-patent References	14.06	1.84	2.61	2.73	3.62	14.43

Table 5. Correlations between key variables (All fields)

		Patents	Publica-tions	Number of publishing KGI's	Number of publishing companies	Popula-tion	Average number of NPRs
Patents	Pearson Correlation	1	0.116	0.199(**)	0.191(**)	0.249(**)	–0.006
	Sig. (2-tailed)	0.0	0.072	0.002	0.003	0.000	0.922
	N	241	241	241	241	239	241
Publications	Pearson Correlation	0.116	1	0.933(**)	0.877(**)	0.229(**)	0.163(*)
	Sig. (2-tailed)	0.072	.	0.000	0.000	0.000	0.011
	N	241	241	241	241	239	241
Number of publishing KGI's	Pearson Correlation	0.199(**)	0.933(**)	1	0.861(**)	0.275(**)	0.160(*)
	Sig. (2-tailed)	0.002	0.000	.	0.000	0.000	0.013
	N	241	241	241	241	239	241
Number of publishing companies	Pearson Correlation	0.191(**)	0.877(**)	0.861(**)	1	0.261(**)	0.102
	Sig. (2-tailed)	0.003	0.000	0.000	.	0.000	0.116
	N	241	241	241	241	239	241
Population	Pearson Correlation	0.249(**)	0.229(**)	0.275(**)	0.261(**)	1	0.080
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	.	0.219
	N	239	239	239	239	239	239
Average number of NPRs	Pearson Correlation	-0.006	0.163(*)	0.160(*)	0.102	0.080	1
	Sig. (2-tailed)	0.922	0.011	0.013	0.116	0.219	.
	N	241	241	241	241	239	241

* Correlation is significant at the 0.05 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).

A similar pattern can be noticed for the number of publishing knowledge generating institutes (KGIs). The number of companies actively involved in the production of scientific papers is considerably lower, but note a relatively high average number of publishing companies in the field of Stem Cells. The following countries are responsible for these higher levels of both number of publications and number of publishing KGIs: USA, Japan, France, Germany and to a lesser extent the United Kingdom. Finally, the average amount of NPRs is highest in pharmaceutical/ /biotechnology related fields (Alzheimer/Tissue Engineering and Stem Cells).

Table 5 reports on the correlations between the different variables that are included in the analysis. First, and this should come as no surprise, population significantly correlates with all other variables – except with the average amount of NPRs. This observation confirms the relevance of including population as a control variable. Second, high correlations are found between the indicators reflecting actors and output of scientific activity: total amount of publications, number of knowledge generating institutes associated with these publications and finally the number of companies associated with these publications. The multicollinearity between these variables inspired us to apply multivariate models with residuals values for number of publishing KGIs and number of publishing companies. Finally, significant but moderate correlations are observed between the average amount of NPRs and the number of publishing KGIs.

Addressing the research questions: does technological performance – on a national level – relate to scientific performance and/or science-technology relatedness?

The central research questions pertain to the relationship between patenting performance on the one hand, and levels of scientific activity (number of publications) as well as science-technology relatedness on the other hand. Science-technology relatedness was measured by: the number of companies actively contributing to scientific activity (publications authored or co-authored by companies); the number of actively contributing knowledge generating institutes (universities or public research organizations) within a certain subfield as well as the (average) amount of non-patent references. In addition, domain differences, country sizes and the impact of the time period considered (year) were taken into account when analyzing the relationship with technological activity.

As stated earlier, a multicollinearity issue arises due to the extremely high correlations between three of the independent variables: the amount of publications, the amount of publishing companies and the amount of publishing KGIs ($r = \pm 0.90$). This implies that the interpretation of the findings obtained for these variables becomes problematic, because their effects are to a large extent interchangeable. In order to assess their distinctive effects; two intermediate regressions were performed with the number of publications acting as an independent variable. The number of publishing companies and the number of KGIs were treated respectively as dependent variables. In a next step, the residual values were calculated both for number of publishing companies and for number of publishing KGIs. In doing so, the influence of the total amount of publications – as reflected in the regression equation – is removed from the amount of contributing actors. As a consequence, the correlation between the number of publications and the (standardized) residual values for number of companies and number of KGIs equals zero.

In a next step, an Ancova analysis (Analysis of Co-Variance) was performed with patent activity as dependent variable and domain and year as fixed factors (categorical data). Covariates are: the amount of publications, the residual values obtained for the number of KGIs and Companies involved in these publications, the average number of NPRs and finally population figures. Table 6 summarizes the results obtained.

Table 6. Results of ANCOVA
Dependent Variable: Patent Activity; Domain and Year as Fixed Factors; All other variables: Covariates. Number of KGIs/Companies involved in scientific research activity: Residual values (corrected for total amount of publications) Time Period: 1997–2001

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	45.260	32	1.414	10.183	0.000
Intercept	2.095	1	2.095	15.084	0.000
Publications	6.094	1	6.094	43.873	0.000
Population	1.256	1	1.256	9.043	0.003
Average Amount of Non-patent References	1.782	1	1.782	12.829	0.000
Number of KGIs involved in scientific activity (Residual Value)	1.393	1	1.393	10.026	0.002
Number of Companies involved in scientific activity (Residual Value)	5.588	1	5.588	40.232	0.000
Domain	9.012	5	1.802	12.977	0.000
Year	5.261	4	1.315	9.470	0.000
Domain * Year	2.023	18	0.112	0.809	0.688
Error	28.613	206	0.139		
Total	208.541	239			
Corrected Total	73.873	238			

R Squared = 0.613 (Adjusted R Squared = 0.553)

As an inspection of Table 6 reveals, several variables significantly relate to patenting performance. A significant relation, which can be assumed to be positive, was found with population size. The appearance of significant domain effects can be considered in line with the average patent volumes as reported in Table 4. More interesting from the perspective of the research questions posed, are the results obtained for the scientific and 'science-technology relatedness' indicators. Both the number of publications and the average amount of NPRs (used as an indicator of science-technology relatedness) are significantly related to technological performance. At the same time, it can be noted that the variables pertaining to the number of actors (KGIs and companies) still significantly relate to technological performance, despite the elimination of shared variance with the total amount of publications. Stated otherwise, the residual values of both the number of publishing companies and the number of publishing KGIs significantly contribute to the variance observed in terms of patent activity, independent from the total amount of publications. Finally, one notes a significant year effect. Considering Table 1, this effect can be assumed to be negative. At the same time Domain*Year interaction effects are not present; implying that the same trend is equally manifest in all domains under study. The hypothesis that the observed year effects are due to the time lag inherent in the granting process of patents – resulting in a significant decline of patent activity after 2000 – is confirmed when performing a similar analysis for the time period 1997–1999 only. The significance of the relationships examined mirrors the findings of Table 6 – except for year, which is no longer significant.

Finally, the regression analysis, complementing the ANCOVA results of Table 6, provides a systematic view on the signs of the observed relationships. Dummy variables were introduced for the different domains, with Femto-Second Lasers acting as reference point. Table 7 indicates positive beta values for the key variables under study: scientific activity and average amount of NPRs. In addition, one observes positive values for both the number of companies and the number of KGIs involved in scientific activity.

Table 7. Regression Results
Dependent Variable: Patent activity
Number of KGIs/Companies involved in scientific research activity: Residual values
(corrected for total amount of publications) Time Period: 1997–2001

Variable	B	SE	Beta	T	Sign T
(Constant)	251.037	46.944		5.348	0.000
Stem cells Y/N	–1.121	0.132	–0.558	–8.477	0.000
Conductive Polymers Y/N	–0.469	0.086	–0.283	–5.423	0.000
Nano Electronics Y/N	–0.227	0.088	–0.176	–2.583	0.010
Fuel Cells Y/N	–0.217	0.081	–0.143	–2.667	0.008
Alzheimer Y/N	–0.476	0.090	–0.307	–5.279	0.000
Year	–0.126	0.023	–0.250	–5.369	0.000
Amount of Publications	0.351	0.061	0.468	5.730	0.000
Average Amount of Non-patent References	0.309	0.071	0.237	4.366	0.000
Population	0.197	0.062	0.219	3.165	0.002
Number of KGIs involved in scientific activity (Residual Value)	0.089	0.027	0.164	3.344	0.001
Number of companies involved in scientific activity (Residual Value)	0.139	0.025	0.254	5.554	0.000

Discussion and directions for further research

As these analyses are of an exploratory nature, additional analyses and verification efforts are advisable (see below) to confirm the robustness of the results obtained. At the same time, the findings presented here are in several ways interesting and promising.

First, the overall explained variance is considerable: the variables introduced in the model explain over 50% of the variance observed in technological activity.

Second, some first intermediate conclusions can be derived, relating to the relevance of the indicators explored and developed. Both the indicators for scientific activity and for science-technology relatedness appear to significantly coincide with variation that is observed in terms of patent activity. Stated differently, countries performing better on a technological level – as measured by the amount of patenting activity – are characterized both by larger numbers of publications and by numbers of involved institutions that exceed average expected[10] values. The latter observation holds for both companies and knowledge generating institutes actively involved in scientific activities. As such, our findings seem to suggest beneficial effects of scientific capabilities shouldered by a multitude of organizations. In addition, higher numbers of patent activity coincide with more NPRs, pointing out the relevance of science 'proximity' when developing technology in newer, emerging fields.

The positive statistical relationship with the number of companies engaged in scientific research activity may come as a surprise, considering the general trend in the business sector to reduce the engagement in more exploratory ('basic') scientific research. Our findings suggest the relevancy – for the performance of national innovation systems – of R&D strategies on the company level implying a minimum level of in-house research and engagement in scientific cooperation with public sector research organizations, public-private joint research ventures or technology development centers. Each of the hot topics dealt with in this analysis are exemplars of knowledge domains and fledging industrial sectors where industry needs to be active at the cutting edge of both basic and applied science for reaping the 'first mover' benefits in competitive global markets (either in terms of acquiring patents, selling licenses, or launching innovative products and processes).

It goes without saying that these findings need to be further corroborated by efforts geared towards confirming and further developing the insights obtained so far. Extending the analyses towards other sub-domains and hot topics seems relevant and may allow further documentation of technology life cycle dynamics and their impact on the relationships found. The authors are currently examining the possibilities to extend the findings by introducing longer time frames: relating scientific, technological

[10] Expected values based on publication volume.

activities and their interactions over time will allow assessing more precisely the (assumed reciprocal) influence of the different activity realms and their effects on performance as well as delineate more precisely the moderating impact of technological life cycle stages.

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