THE UNIVERSITY OF MELBOURNE

FACULTY OF BUSINESS & ECONOMICS

Melbourne Institute Working Paper Series

Working Paper No. 15/13

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MELBOURNE INSTITUTE® of Applied Economic and Social Research

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Melbourne Institute Working Paper No. 15/13

ISSN 1328-4991 (Print)

ISSN 1447-5863 (Online)

ISBN 978-0-7340-4305-4

April 2013

* A slightly modified version of this paper is forthcoming in *Industrial and Corporate Change*. Please consult the published version. An earlier version of this paper circulated under the title "The R&D-patent relationship: An industry perspective". The authors are indebted to Bronwyn Hall, Hubert Strauss, Eric Perée, and two anonymous referees for very useful comments on an earlier version of the paper. The paper has benefited from comments made by participants at various seminars and conferences, including the 2009 EIB Conference in Economics & Finance (Luxembourg), the 2010 Competition and Innovation Summer School (Turunç), the 2010 IPTS Patent Workshop (Seville), and the 2011 Second Asia-Pacific Innovation Conference (Singapore). The authors also gratefully acknowledge financial support from the European Investment Bank. For correspondence, contact Dr de Rassenfosse, email <gaetand@unimelb.edu.au>.

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Abstract

This paper decomposes the R&D-patent relationship at the industry level to shed light on the sources of the worldwide surge in patent applications. The empirical analysis is based on a unique dataset that includes 5 patent indicators computed for 18 industries in 19 countries covering the period from 1987 to 2005. The analysis shows that variations in patent applications reflect not only variations in research productivity but also variations in the appropriability and filing strategies adopted by firms. The results also suggest that the patent explosion observed in several patent offices can be attributed to the greater globalization of intellectual property rights rather than to a surge in research productivity.

JEL classification: O30, O34, O38

Keywords: Appropriability, complexity, patent explosion, propensity to patent, research productivity, strategic patenting

1. Introduction

Patent-based indicators are increasingly used to assess the rate of technological change, to gauge firms' competitive positions, or to study knowledge spillovers. The success of patent statistics is rooted in their wide availability, their intrinsic links to inventions, and their relatively homogeneous standards across countries. International treaties, such as the Paris Convention for the Protection of Industrial Property of 1883 or the Patent Cooperation Treaty (PCT) signed in 1978, have set some legal and quality standards across patent offices worldwide. Empirical studies on the R&D-patent relationship performed on cross-sectional or panel data unambiguously lead to the conclusion that there is a significant correlation between R&D inputs and patent counts, although the estimated elasticity varies greatly with the econometric specifications adopted.

The idea that patents are relevant indicators of technological change is not without its detractors. It is well known that not all inventions are patentable and that not all patentable inventions are actually patented. There are noticeable differences in the use of patents across firms, industries, and countries, which make patent data rather difficult to interpret. In addition, patented inventions differ in terms of their quality, or "inventive step," and their economic significance. Concerns about the use of patents as economic indicators have been further reinforced by the greater emphasis on strategic patenting in the literature (e.g. Hall and Ziedonis, 2001; Blind et al., 2006). Surely the significant increase in the number of patent filings observed worldwide over the last two decades is not entirely explained by an increase in R&D expenditures (Kortum and Lerner, 1999; Hall, 2005; WIPO, 2011).

This paper aims to decompose the R&D-patent ratio into its many components in order to shed light on the sources of growth in patenting activity. Its contribution to the literature is both conceptual and empirical. On the conceptual level, we acknowledge that patent numbers reflect not only research productivity but also strategic considerations, such as the proportion of *inventions* patented (the "appropriability strategy") and the number of patents filed to protect an *innovation* (the "filing strategy"). For instance, firms in the telecommunications industry patent many inventions and typically have a myriad of patents for any one product (e.g., the mobile phone). In contrast, firms in the pharmaceutical industry patent many inventions, but drugs are generally protected by a small number of key patents. While many surveys measure the appropriability strategy (e.g., Levin *et al.*, 1987; Arundel and Kabla, 1998; Cohen *et al.*, 2000), the filing strategy has rarely been considered thus far. Furthermore, although the filing strategies of firms have been studied by several authors (e.g., Hall and Ziedonis, 2001; Reitzig, 2004), their effect on the R&D-patent relationship has been largely neglected.

The empirical contribution of the paper is twofold. First, this paper evaluates the R&D-patent relationship using a unique panel dataset covering 18 industries in 19 countries over 19 years (1987–2005). Most studies on the determinants of patenting activity are performed at the firm, regional, or country levels. Only rarely do such studies cover the industry level.[1] While intellectual property strategies differ across firms, especially across firms of different sizes, they also vary widely across industries. Second, this study relies on five patent-based indicators – some of which are new – to further understand the nature of the patent explosion: priority filings, EPO filings, USPTO filings, "regional" filings (a combination of EPO and USPTO filings), and triadic filings.[2] A priority filing is the first patent application protecting an invention. A subsequent patent application can then be filed at regional offices (such as the European patent office (EPO) for European applicants or the US Patent Office (USPTO) for North American applicants) or simultaneously at the three offices (the USPTO, the EPO and the Japanese Patent Office (JPO), or the so-called triadic patents) and covers a broader geographical area. The average quality or value of patent indicators is low for priority filings and higher for triadic applications, because of the higher legal and attorney fees, as well as translation costs arising from the broader geographic protection.

The econometric analysis is conducted in two stages. The first stage involves estimating the determinants of the patent production function. The results confirm that the research productivity dimension matters and that it explains part of the variation in the patent-to-R&D ratio at the industry level. This finding serves as additional evidence that patents are valid economic indicators that can be used to measure technological progress. The long-term

[1] To the best of our knowledge, Meliciani (2000) offers the only panel-based econometric analysis at the industry-level. The sample covers 15 industries in 12 countries over 20 years. The lack of studies at the industry level can partly be explained by the difficulty faced by researchers in matching patents with industry-level data: patents are not classified by economic sectors, and the correspondence between technological and economic nomenclatures is not straightforward.

[2] "Regional" filings are those made at either the EPO or the USPTO, or a mix of both, as explained in section 3.2. These two patent offices attract a large number of applications from non-domestic applicants—about half of the total number of filings in the two offices.

elasticity of patents with respect to R&D is about 0.12. The results also confirm that the inclusion of the two components of the propensity to patent – appropriability and filing strategies – helps to refine the link between R&D and patents. This finding sheds light on the strong variability in the patent-to-R&D ratio across industries and suggests that patent indicators are affected by 'strategic' considerations.

In the second stage, we use the regression results to decompose the sources of growth in patenting activity. We find that R&D expenditures account for a modest share of the variance in patenting (from 1 to 5 per cent depending on model specifications) compared to the variables which control for research productivity and propensity to patent. Moreover, our analysis of the fixed effects related to the three dimensions of our panel dataset, which capture a large share of the variance in patent growth, provides additional insights into the sources of growth. While some industries (computers and communication technologies) and countries (South Korea, Spain, and Poland) have experienced a drastic increase in patent applications, the ratio of priority patent applications to R&D expenditure has been generally constant. This result suggests that there has been no spurt in innovation productivity. In contrast, regional applications (filings at the USPTO or at the EPO) have been increasing since the early 1990s, suggesting that the patent explosion observed in large regional patent offices is due to the greater globalization of intellectual property rights rather than a surge in research productivity.

The paper is structured as follows. The next section surveys key empirical studies on the R&D-patent relationship and introduces the conceptual approach. Section 3 presents the empirical model, the five patent indicators and the explanatory variables. The empirical results are presented and interpreted in section 4. Section 5 presents the conclusions, as well as a discussion of research and policy implications.

2. The components of the R&D-patent relationship

Many empirical studies have investigated the relationship between R&D and patents using the methodology first proposed by Pakes and Griliches (1980) as illustrated in Table A1 in Appendix 1. Pakes and Griliches estimated a knowledge production function that models patent count as a function of current and past research expenditures. The estimated elasticity of patents with respect to R&D is generally found to be positive and significant, but its amplitude varies greatly depending on the econometric specifications adopted. The wide variation is striking with firm-level analyses (see, for example, Hausman et al., 1984; Hall et al., 1986; Jaffe, 1986; Cincera, 1997; Duguet and Kabla, 1998; Crépon et al., 1998; Blundell et al., 2002; Czarnitzki et al., 2009) as well as in more aggregate levels of analyses (see, for instance, de Rassenfosse and van Pottelsberghe, 2009, at the country level, and Bottazzi and Peri, 2003, at the regional level).

Few scholars have studied the R&D-patent relationship at the industry level. An exception is Meliciani (2000), who studies variations in USPTO patents across countries, industries, and over time. The author shows a quite low – but positive and significant – elasticity of R&D. She also points out that patterns of innovation are sector-specific rather than country-specific: the variability of relative measures of R&D and of patenting performance is larger across sectors than across countries. Other studies have also illustrated the strong variations in patents-to-R&D ratio across industries.[3] Kim and Marschke (2004) have shown for instance that the pharmaceutical industry presents a low patent-R&D ratio (with 166 patents per billion R&D dollar in 1992) compared to other industries, especially cumulative technology industries (e.g. electronic instrument and communication equipment, computers and computational equipment). In addition to yielding a large number of patents per dollar of R&D, the latter industries have experienced a stronger growth of their patents-to-R&D ratio.

Five potential explanations may account for the fluctuation in the estimated elasticity. First, R&D indicators encompass much more than the activity of generating new ideas and inventions. Therefore, R&D might not be a good indicator of innovative effort. Second, R&D expenditures represent only a fraction of the total resources a firm devotes to innovative activities. On the basis of detailed data for the Netherlands in 1992, Brouwer and Kleinknecht (1997) estimated that R&D expenditure represented about one-quarter of total innovation expenditure. Sirilli and Evangelista (1998) reported that R&D expenditure accounted for 36% of total innovation expenditure in Italian manufacturing firms. Investments in fixed assets, market research, and trial production are as many expenses that are not accounted for in official statistics. See also Cincera (1998) for similar figures. Third, patent series are, by their very nature, subject to a substantial bias, as most patents generate low or no value and only a

[3] See also Table 3 in the next section.

few patents are associated with a high economic value. Fourth, more generally, the estimates could also be affected by the patent count methodology that is used (see de Rassenfosse *et al.*, 2012 for a recent detailed explanation of existing patent counts).

A fifth concern relates to the strong influence of the propensity to patent in the R&D-patent relationship (e.g., Hall and Ziedonis, 2001). The R&D-patent relationship can be decomposed in two main dimensions: the productivity of the research efforts which can potentially lead to inventions and the propensity to patent in order to protect a given innovation. Scholars have long argued that patent counts reflect more the latter dimension than the former one. For instance, Scherer (1983, p 116) explicitly assumed that research productivity was constant for the sake of simplicity. While admitting the possibility of “differential creativity of an organization’s R&D scientists and engineers,” the author did not consider this element. Instead, Scherer chose to concentrate on other, “more systematic” factors. In Scherer’s study, the more “systematic” factors that drove the patenting performance of firms were related to the propensity to patent.

In this paper we explicitly model the two dimensions of the R&D-patent relationship: the productivity of research on the one hand, and the propensity to patent, defined as the number of patents per innovation, on the other hand. The propensity to patent is itself composed of two dimensions: the decision to protect an *invention* with a patent and the number of patented inventions per *innovation*. We refer to the former as the “appropriability strategy” and to the latter as the “filing strategy.” It is important to emphasize the distinction between invention and innovation. While the former relates to an improvement in knowledge, the latter refers to a final product and is usually composed of a set of inventions and, thus, potentially encompasses several patent filings.

A decision to patent an invention (appropriability strategy) is largely determined by the efficacy of patent protection to appropriate innovation rents. Companies rely on numerous mechanisms of rent appropriation, such as secrecy, lead time, complementary sales and services, complementary manufacturing facilities, barriers to entry, and tacit knowledge (e.g., Teece, 1986). These mechanisms may coexist with patent protection and are often paired with it. In the Carnegie Mellon Survey undertaken by Cohen *et al.* (2000), secrecy and lead time were found to be the two most effective appropriability mechanisms, and were top ranked in 17 and 13 industries, respectively. Patent protection generally appears to be the least effective mechanism, although its importance varies significantly across industries (see Table 1). Patent protection is particularly important for pharmaceutical, chemical, and precision instrument firms. Based on survey data gathered from R&D executives in Switzerland, Harabi (1995) reported that the ability of competitors to invent around patents and the perception that patent documents disclose too much information were the most important factors that limited the use of patents.

Nevertheless, an application for a patent is not always only driven by a desire to protect innovation rents; other motivations, related to the alternative roles of patents, encourage firms to seek patent protection. Patents can be used as a tool for technology negotiations with competitors or potential collaborators, to exclude rivals from a particular technology area, for communication and marketing purposes, to increase revenues through license agreements, to ensure the freedom to operate, or to attract investors. These considerations all influence the observed patenting performance of firms (see, for instance, Cohen *et al.*, 2000; Hall and Ziedonis, 2001; Blind *et al.*, 2006; or de Rassenfosse, 2012, for detailed investigations in this field).

Once a decision is made to protect an invention, the applicant chooses the number of patents that are to be filed. We refer to this step as the "filing strategy." Reitzig (2004) provided early evidence that this dimension matters. On the basis of survey data for 614 patents filed at the EPO, Reitzig found that innovations were protected by a coherent group of around five patents on average. In addition to the decision on how many patents to file, the applicant must also consider the necessary geographical scope of protection, i.e., in which countries patent protection should be sought.

To summarize, we identify two key milestones when analyzing the R&D-patent relationship. The first milestone is the distinction between research productivity and patent propensity. The second milestone is the distinction between appropriability and filing strategies.

Table 1. Share of inventions that are patented (in percentages)

	Arundel and Kabla (1998)	**Cohen *et al.* (2000)**
Mining	28	-
Food, beverages, and tobacco	26	15
Textiles and clothing	8	9
Petroleum refining	23	38
Chemicals	57	51
Pharmaceuticals	79	95
Rubber and plastic products	34	40
Glass, clay, and ceramics	29	43
Basic metals	15	4
Fabricated metal products	39	49
Machinery	52	38
Office and computing equipment	57	39
Electrical equipment	44	44
Communication equipment	47	51
Precision instruments	56	52
Automobiles	30	51
Other transport equipment	31	-
Power utilities	29	-
Transport and telecom services	20	-

Notes: The industry classification corresponds to that presented in Arundel and Kabla (1998). Figures from Cohen *et al.* (2000) were averaged across sub-industries when Cohen *et al.*'s industry classification system did not match Arundel and Kabla's system.

3. Empirical implementation

The aim of the empirical analysis is to decompose the R&D-patent relationship taking the factors that affect the productivity of research efforts and the propensity to patent into account. In an ideal set-up, one would be able to observe both the number of inventions and the number of patents. However, as the only observable measure of inventive output is the patent count, one should be cautious when interpreting the parameters of the patent-production function because differences in patent numbers reflect both productivity and propensity effects.

3.1 The model

The dataset has three dimensions: time (*t = 1,…, 19*), industry (*i = 1,…, 18)*, and country *(j = 1,…, 19)*. Each "individual" thus reflects an industry–country pair.[4] As research efforts (*R*) lead to inventions (*I*), which, in turn, may lead to patent applications (*P*), the R&D-patent relationship for the N individuals in the sample can be expressed as follows (temporarily excluding the time dimension):

$$I = \Omega R^{\gamma} \text{ and } P = \Phi I, \tag{1}$$

where the parameter γ is a scalar measuring the average return to R&D across individuals, and Ω and Φ are diagonal matrices of size N capturing the productivity and the propensity effects for each individual, respectively.[5] In this framework, the matrix Φ captures both the appropriability strategy and the filing strategy. It can also be expressed as a function of the two propensity components, but this would unnecessarily clutter the notation. If we let X and Z, respectively, denote the matrices of variables that affect Ω (productivity) and Φ (propensity), and if we let α and β, respectively, reflect the column vectors of coefficients, then equation (1) can be written as:

$$i = c_1 + \alpha\, x + \gamma\, r \text{ and } p = c_2 + \beta\, z + i, \tag{2}$$

where the lower-case Roman letters denote the logs of the variables. If we expand the patent-production function, we arrive at:

$$p = c + \gamma\, r + \beta\, z + \alpha\, x, \tag{3}$$

[4] An alternative approach would be to estimate the parameters of a patent-production function for each industry, thereby allowing for differentiated impacts across industries. Nevertheless, the "pooled" approach was chosen because it is based on a larger number of observations and provides averages across industries and countries. It is the purpose of this paper to grasp cross-industry determinants of patent-to-R&D variation.

[5] The expression R^{γ} indicates that each of the N elements r_{ij} of *R* is taken to the power of γ.

where $c = c_1 + c_2$ is a scale parameter capturing the rate at which research efforts lead to patent applications (c_1 reflects the average productivity of research across individuals and c_2 reflects the average propensity to file patents). As suggested in the literature (see the introduction and section 2), the propensity to patent has most probably increased since the 1980s due to an unobservable greater reliance on the patent system for various strategic reasons. In other words, c_2 may have increased over time even after accounting for the observable characteristics Z. Along a similar vein, research productivity has probably improved over the years (Kortum and Lerner, 1999). Therefore, the extent to which the scale variable c can capture the average growth rate of the productivity of research or of the two propensity effects is unclear. At this stage, we remain agnostic as to what the variable c captures. However, we analyze its various dimensions (country, industry, and year) in greater detail in section 4.2 in order to shed light on the sources of the patent explosion.

The patent-production function for a given industry-country pair at a single point in time (*ijt*) can be written as:

$$p_{ijt} = c_{ijt} + \gamma\, r_{ijt} + \beta\, z_{ijt} + \alpha\, x_{ijt} + \varepsilon_{ijt}\,, \tag{4}$$

where ε_{ijt} is the error term. It is good practice to estimate panel data using first differences to avoid potential spurious-regression problems. If we let Δ denote the first-difference operator, equation (4) can be transformed as follows:

$$\Delta p_{ijt} = \Delta c_{ijt} + \gamma\, \Delta r_{ijt} + \beta\, \Delta z_{ijt} + \alpha\, \Delta x_{ijt} + \upsilon_{ijt}\,, \tag{5}$$

with $\upsilon_{ijt} = \Delta\varepsilon_{ijt}$. As the variables are expressed in logs, equation (5) is an approximation of the growth rate of patenting. The term Δc_{ijt} is the growth rate of patent filings that is not accounted for by the explanatory variables. Equation (5) implies that a change in any of the explanatory variables has a contemporaneous impact on the number of patent applications. In other words, the parameters of the first-differenced variables capture the short-term elasticities.

Given that the R&D-patent process is co-integrated, the patent-production function is estimated by means of an error correction model (ECM) with a one-year lag structure.[6] The ECM provides a rich econometric framework that allows for the estimation of both short-term and long-term elasticities. The choice of a one-year lag is motivated by Hall *et al.* (1986).[7] These authors estimated several panel data models at the microeconomic level and obtained evidence of a strong contemporaneous relationship between R&D expenditure and patenting, and of a small effect of R&D history on patent applications. This is consistent with the practice of starting to file patents early in the life of a research project, although the lag between initial R&D expenditures and patent applications can admittedly be much longer.

The ECM involves estimating the model in first differences together with the previous year's deviation from equilibrium (in parentheses), which leads to the following equation:

$$\begin{aligned}\Delta p_{ijt} = \psi_i + \psi_j + \psi_t + \gamma_s \, \Delta r_{ijt} + \beta_s \, \Delta z_{ijt} + \alpha_s \, \Delta x_{ijt} \\ - \lambda \left(p_{ijt-1} - c - \gamma_l \, r_{ijt-1} - \beta_l \, z_{ijt-1} - \alpha_l \, x_{ijt-1} \right) + \nu_{ijt}.\end{aligned} \quad (6)$$

Remember that the individual is defined as a country-industry pair. The term Δc_{ijt} in equation (5) is decomposed into a fixed industry effect (ψ_i), a fixed country effect (ψ_j), and a common time effect (ψ_t) in equation (6).

The term in the parentheses in equation (6) is usually referred to as the error correction term. It can be interpreted as the deviation from equilibrium in the previous period. The variables expressed in first difference – those preceded by the operator Δ – capture the short-term impact on the number of patents. In other words, they indicate how a change in any explanatory variable contemporaneously affects the number of patents. The parameter λ usually fluctuates between 0 and 1, and measures the speed of adjustment to the long-term equilibrium (the closer to 1, the quicker the adjustment process). The long-run elasticities are calculated by dividing each estimated parameter associated with the lagged variables by the adjustment parameter λ (for a discussion, see Alogoskoufis and Smith, 1991).

[6] The tests on unit roots and co-integration for our panel data suggest that the series are non-stationary and co-integrated (see Appendix 2).

[7] Kondo (1999) analyzes the dynamic mechanism of the R&D-patent relationship of Japanese industry and shows that R&D effort leads to patent applications with a time-lag of about one and a half years.

3.2 The dependent variable: patent indicators

Many ways of counting patents exist, each with its own strengths and weaknesses (see, for example, Dernis *et al.,* 2001, and OECD, 2009, for a discussion). It is therefore particularly important to carefully select the patent indicators to be used to monitor innovation performance so as to reduce the potential biases as much as possible. Five alternative indicators are used in this empirical analysis in order to gauge the robustness of the results to the chosen dependent variable. These indicators are: the number of national priority filings, the number of patents filed at the EPO, the number of patents filed at the USPTO, a measure combining EPO and USPTO patents, and the number of patents filed simultaneously in Japan, the US, and Europe ("triadic" patents). Whereas the first indicator is composed of many patents with a highly skewed distribution of value, triadic filings are less numerous but are of a much higher economic value. Note that we focus on patent filings rather than on granted patents, so that the patent count is not affected by varying grant rates across patent offices or over time. The patent counts are assigned to the country of inventor(s) and are also expressed by priority year so that they better reflect the date of invention.

The patent indicators are computed from the OECD-EPO PATSTAT database (April 2009) for each manufacturing industry following the International Standard Industry Classification scheme (ISIC, Revision 3), as indicated in Table A2 of Appendix 1. However, patents are not classified using the ISIC scheme but rather using the codes of the International Patent Classification (IPC) scheme, which represent the different areas of technology to which they pertain. Patents have therefore been assigned to the appropriate industries using the concordance table between IPC and ISIC codes provided by Schmoch *et al.* (2003). Schmoch *et al.* estimated the empirical concordance table by investigating the patenting activity in technology-based fields (IPC) of more than 3,000 firms classified by industrial sector (ISIC). When a patent contains more than one IPC code, the industry allocation is performed on a fractional basis.[8]

The first indicator is the corrected count of national priority filings (NPFCORR), which was recently introduced by de Rassenfosse *et al.* (2012). This indicator captures all of the patents

[8] Some patents had no IPC codes and some IPC codes were not in the concordance table. All "unassigned" patents were allocated to industries according to the observed share of successfully allocated patents.

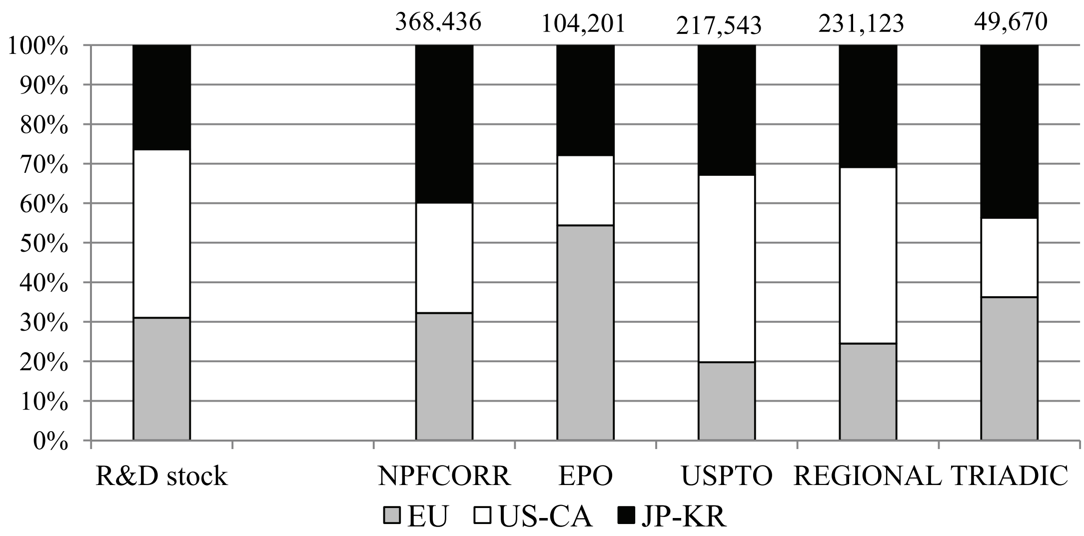
"invented" in a country, regardless of the patent office of application. For example, the count for Austria is equal to the number of priority filings made by inventors based in Austria and filed at the Austrian patent office plus the priority filings made by inventors based in Austria but filed directly at other patent offices, such as the EPO, the USPTO, or the German patent office. This methodology assures the best match between R&D expenditure and patent applications at the country level. The inclusion of priority filings made abroad also reduces the bias against small countries, such as Belgium and the Netherlands, which file a higher share of their patents abroad than larger countries, such as France or Germany. This worldwide count of priority filings is a broad measure of patenting that encompasses both low-value and high-value patents. It is biased in favor of Japan and South Korea, as the share of these countries in the total number of national priority filings is much higher than their share of R&D expenditures. The patent systems in these countries favor patents that are much smaller in scope but more numerous. On average, patents filed at the Japanese and the Korean patent offices have one-third the number of claims than patents filed at the USPTO or the EPO. For this reason, the count for Japanese and Korean priority filings has been divided by three (for a discussion, see Kotabe, 1992, and Archontopoulos *et al.*, 2007).[9]

The second indicator is the count of patent applications filed at the EPO. This indicator is composed of the patents that were filed directly at the EPO and those that were extended to the EPO as second filings. As the EPO patenting procedure is expensive, EPO patents are generally of a higher value. This indicator is biased for two main reasons. The first is related to home bias, as companies in Europe tend to file a higher proportion of their patents at the EPO than companies from non-European countries (see Figure 1). de Rassenfosse, Schoen and Wastyn (2013) presented firm-level evidence that a count of EPO patents provided biased estimates of patent production functions. Second, the reliance on the EPO has increased over time for all countries, especially those in Europe. In this respect, de Rassenfosse and van Pottelsberghe (2007) showed the presence of a systematic bias in statistics based on European patents: the share of priority filings transferred to the EPO increases with the country's age of membership in the European Patent Convention. This calls for a cautious interpretation of the evolution of the number of EPO patents over time.

[9] As the dependent variable is the growth rate of patent applications, the econometric estimates are not affected by the normalization.

The third indicator is similar to the second except that the patent office of reference is the USPTO. For this indicator, long-term statistics are available for granted patents only. Given that many countries in the sample are European, this indicator probably reflects the value of patents better (a European applicant will find it easier to file at the EPO than at the USPTO and will seek a US patent only for the most valuable inventions).[10] However, this indicator is subject to an important, and logical, home bias for North American applicants, as illustrated in Figure 1.

Figure 1. Research effort and patenting activity



Source: Own calculations based on data for the year 2005.

Note: The count for Japanese and Korean priority filings (NPFCORR) has been divided by three.

The fourth indicator (REGIONAL) is a mix of EPO and USPTO patents. As European applicants are more likely to file at the EPO and as other countries preferably file at the USPTO, the indicator is composed of EPO patents for European countries and USPTO patents for other countries. This mitigates the home biases that characterize the EPO and the USPTO indicators and allows for a geographical distribution that is closer to the actual distribution of research efforts.

The count of triadic patent families is the fifth indicator (TRIADIC). It was developed by the OECD to select patents of high quality that were comparable across countries. According to

[10] To mitigate the effect of the grant lag in US patent statistics, which was especially strong in 2004 and 2005, the data are adjusted for each country-industry pair using the ratio of EPO patents to US patents for the year 2003.

the OECD definition, the triadic patent family is “a set of patent applications filed simultaneously at the EPO, the JPO, and granted by the USPTO” that share one or more priority applications (OECD 2009, p 71). This indicator is more robust to differences in patent regulations across countries and changes in patent laws over time. Triadic patents are of high value given the high cost associated with applying for patents in the three patent offices. On average, only between 10% and 15% of priority filings ultimately become triadic patents. In 2005, the 19 countries included in the sample had a total of 368,436 priority filings for 49,670 triadic patent applications.

The absolute number of patents, their relative shares across countries and industries, and their compound annual growth rates over the period from 1987 to 2005 are presented in Tables A3 and A4 in Appendix 1. These tables show that the so-called patent explosion has taken place in most countries, in all industries, and for all patent indicators. More interestingly, Tables 2 and 3 offer an overview of the patent-R&D ratio across countries and industries in order to illustrate some stylized facts about the R&D-patent relationship. First, the variability of the ratio – and of its growth rate between 1987 and 2005 – across countries (Table 2) and industries (Table 3) indicates that variations in patents are not only driven by change in R&D expenditures. Second, our panel dataset validates and generalizes the industry-level analysis of Kim and Marschke (2004) on USPTO patents by US firms over the period 1983–1992. While a few industries, such as computing machinery (COMP), exhibit both a high patent-R&D ratio and a strong increase in this ratio, other industries have experienced a strong decrease of their relative number of patents. For instance, the patent-R&D ratio in pharmaceuticals decreased at approximately 5% per annum. As pointed out by Kim and Marschke (2004), such decrease is probably explained by the fact that the cost of developing new drugs has been increasing strongly rather than by a lower propensity to patent new drugs.

Table 2. Patent per R&D expenditures (in millions of 2000 USD) by country

	NPFCORR		EPO		USPTO		TRIADIC		REGIONAL	
	Y05	**CAGR**	**Y05**	**CAGR**	**Y05**	**CAGR**	**Y05**	**CAGR**	**Y05**	**CAGR**
AT	0.88	-2.0%	0.48	0.1%	0.18	-1.5%	0.31	2.2%	0.48	0.1%
BE	0.60	2.1%	0.43	3.9%	0.13	2.6%	0.31	4.5%	0.43	3.9%
CA	0.91	0.1%	0.18	0.0%	0.06	-3.5%	0.59	0.5%	0.59	0.5%
DE	1.40	3.1%	0.70	5.1%	0.20	3.4%	0.49	5.8%	0.70	5.1%
DK	0.89	-2.7%	0.59	3.0%	0.18	1.3%	0.53	3.4%	0.59	3.0%
ES	0.65	-2.7%	0.24	4.6%	0.05	2.3%	0.14	2.7%	0.24	4.6%
FI	0.86	-4.9%	0.36	0.6%	0.10	-1.8%	0.36	0.2%	0.36	0.6%
FR	0.79	-0.5%	0.42	1.3%	0.14	0.4%	0.30	1.7%	0.42	1.3%
GB	1.30	-0.7%	0.36	0.8%	0.13	0.1%	0.40	2.6%	0.36	0.8%
IE	0.78	-12.2%	0.33	-0.9%	0.11	-0.9%	0.37	0.4%	0.33	-0.9%
IT	1.80	4.0%	0.75	7.0%	0.13	2.7%	0.41	6.5%	0.75	7.0%
JP*	1.43	-2.7%	0.30	-0.4%	0.23	1.5%	0.67	0.3%	0.67	0.3%
KR*	1.84	6.1%	0.28	17.8%	0.17	16.8%	1.00	10.3%	1.00	10.3%
NL	1.41	4.3%	0.92	4.8%	0.55	5.2%	0.80	5.5%	0.92	4.8%
NO	1.78	1.4%	0.60	7.1%	0.21	5.4%	0.69	6.9%	0.60	7.1%
PL	1.65	-7.9%	0.23	15.8%	0.02	12.0%	0.17	20.3%	0.23	15.8%
SE	0.51	-4.8%	0.33	0.8%	0.12	-0.1%	0.27	0.4%	0.33	0.8%
US	0.70	3.4%	0.12	0.4%	0.07	-1.8%	0.71	3.8%	0.71	3.8%

Source: Own calculations

Notes: * The number of priority fillings for Japan and Korea has been divided by 3. The columns labeled 'Y05' report the patent-R&D ratio in the year 2005 while the columns labeled 'CAGR' report the compound annual growth rate of the patent-R&D ratio over the largest available period. CH was excluded because of lack of R&D data.

Table 3. Patent per R&D expenditures (in millions of 2000 USD) by industry

	NPFCORR		EPO		USPTO		TRIADIC		REGIONAL	
	Y05	**CAGR**	**Y05**	**CAGR**	**Y05**	**CAGR**	**Y05**	**CAGR**	**Y05**	**CAGR**
FOOD	1.00	-3.7%	0.27	-3.5%	0.12	-4.3%	0.52	-2.6%	0.53	-3.1%
TEXT	1.28	0.2%	0.32	1.8%	0.14	0.2%	0.66	1.3%	0.72	1.6%
WPAP	0.82	-2.6%	0.23	-1.0%	0.10	-2.4%	0.42	-1.4%	0.47	-1.2%
PETR	1.61	4.7%	0.53	5.4%	0.26	4.2%	0.90	5.4%	0.96	5.5%
CHEM	1.61	1.8%	0.54	2.6%	0.27	1.9%	0.90	2.8%	0.97	2.8%
PHAR	0.36	-5.3%	0.15	-4.8%	0.08	-6.0%	0.24	-4.4%	0.25	-4.2%
RUBB	1.15	-1.6%	0.32	0.0%	0.13	-1.6%	0.54	-1.0%	0.61	-0.6%
MINE	2.27	2.9%	0.62	4.7%	0.28	3.4%	1.22	4.9%	1.33	5.0%
META	1.71	2.0%	0.48	4.1%	0.22	2.9%	0.90	3.9%	0.98	4.1%
FABM	2.72	0.8%	0.70	3.3%	0.25	1.3%	1.21	1.4%	1.40	1.9%
MACH	1.66	-2.6%	0.44	0.1%	0.18	-1.5%	0.84	-1.0%	0.93	-0.7%
COMP	2.81	5.1%	0.65	6.1%	0.35	5.3%	1.90	8.5%	1.92	8.3%
ELEC	1.03	1.8%	0.27	4.3%	0.13	3.0%	0.63	4.4%	0.67	4.5%
COMM	1.32	-0.4%	0.35	2.0%	0.18	0.7%	0.90	1.1%	0.92	1.1%
INST	0.53	-1.5%	0.14	0.3%	0.07	-0.8%	0.32	0.5%	0.34	0.6%
AUTO	0.64	-0.6%	0.17	2.3%	0.08	0.6%	0.32	0.3%	0.36	0.7%
TRAN	0.35	-0.1%	0.10	3.8%	0.04	2.6%	0.19	1.7%	0.21	1.8%
MISC	3.21	-1.6%	0.52	-0.1%	0.19	-0.3%	1.48	3.2%	1.60	3.1%

Source: Own calculations

Notes: The columns labeled 'Y05' report the patent-R&D ratio in the year 2005 while the columns labeled 'CAGR' report the compound annual growth rate of the patent-R&D ratio over the largest available period.

3.3 Explanatory variables

The most important explanatory variable is the amount of R&D expenditure by country-industry pair (R&D), which measures the research efforts. This variable is taken from the OECD's ANBERD database and is expressed in constant 2000 US dollars (USD) at purchasing power parity (PPP). We use R&D stocks computed using the perpetual inventory method with a depreciation rate of 15%. The use of R&D stocks is motivated by the fact that the patent outcome is the result of an accumulated stock of knowledge over time and not simply the result of recent R&D activities. Estimations undertaken with R&D flows lead to similar results.

The estimated elasticity of patents with respect to R&D provides an incomplete evaluation of research productivity. A more complete picture could be derived if inventions (rather than patents) could be accurately measured or if the two types of propensity to patent were properly measured across countries and over time. As no such indicators are available, an indirect approach is necessary. This consists of finding variables that arguably induce (or reflect) differences in the productivity of research activities and variables that are correlated with the propensity to patent.

Explanatory variables that could affect the propensity and the productivity components for a large group of countries are hard to find, especially variables that vary over industries and that are available over a long period of time. Moreover, it is also difficult to find indicators that impact only one component and not the other. Despite these limitations, three candidates that might affect the productivity of research and four that could affect the propensity to patent were identified. Some vary over time and across countries and industries, whereas some others vary only across one dimension, as indicated in Table 4.

Table 4. Overview of the explanatory variables

	Component		**Variation**		
	Productivity (x)	***Propensity (z)***	***Country***	***Industry***	***Year***
R&D STOCK			x	x	x
SHARE HIGHER EDU	x		x		x
SHARE BASIC	x		x		x
RCA	x		x	x	x
APPROPRIABILITY		x		x	
COMPLEXITY		x		x	x
IP INDEX		x	x		x
QUALITY		x	x		

Source: Own computations of the stocks based on OECD STAN R&D Expenditure in Industry (ISIC Rev. 3), ANBERD ed2009 for R&D STOCK; and OECD Main Science & Technology Indicators for SHARE HIGHER EDU and SHARE BASIC. Own computation based on OECD STAN Bilateral Trade Database for RCA; Arundel and Kabla (1998) for APPROPRIABILITY; von Graevenitz et al. (2011) for COMPLEXITY; Park (2008) for IP INDEX, with yearly data computed on the basis of a compound annual growth rate between two available data points; de Saint-Georges and van Pottelsberghe (2012) for QUALITY.

The three variables that are assumed to affect – or correlate with – research productivity are defined and measured as follows. The variable "SHARE HIGHER EDU" is defined as the percentage of gross domestic expenditure on R&D that is undertaken by the higher education sector (OECD Main Science & Technology Indicators (MSTI) 2009). The expected impact on the number of patents is ambiguous. On the one hand, the higher education sector develops and utilizes frontier knowledge that private companies can use, suggesting a positive relationship. On the other hand, the propensity to patent is lower among universities, such that a negative impact is also possible. The second productivity variable, "SHARE BASIC," reflects basic-research expenditure as a percentage of gross domestic expenditure on R&D (OECD MSTI). A higher value for this variable is expected to lead to greater productivity in research efforts, as basic research typically pushes the knowledge frontier and generates opportunities for further development. The third productivity variable is "RCA," which measures the "revealed comparative advantage" of each country across different industries. It is defined for each country *i*–industry *j* pair as the ratio of the share of industry *j* in the export of country *i* to the share of industry *j* in world exports (own computation based on the OECD STAN Bilateral Trade Database). A ratio higher than one reveals a comparative advantage, as the country exports relatively more in that particular industry, suggesting that it is internationally competitive. A positive correlation is expected, as internationally competitive industries must be innovative in terms of new product performance or reduced production costs. In analyzing the determinants of patenting across a set of OECD countries, Furman *et al.* (2002: 899) found that "an extremely important role is played by factors associated with differences in R&D productivity [such as] openness to international trade." Note that the RCA variable could be endogenous to the patenting activity because innovations increase export opportunities. This concern is addressed in the empirical analysis by estimating an ECM with lagged values of explanatory variables.

Four proxies are used to measure the propensity effects. The first variable, "APPROPRIABILITY," captures the *appropriability strategy* by industry and is based on a survey of the proportion of inventions that were patented in the French manufacturing sector (Arundel and Kabla, 1998). This observation reduces the noise in the R&D-patent relationship by directly correcting for a fundamental link between inventions and patents. This data source is preferred over Cohen *et al.* (2000) because it is the closest to the industry classification found in the ANBERD database. To the best of our knowledge, there exists no systematic industry-level data on the *filing strategies* of firms – the number of patent applications per innovation. A closely related concept is the discrete versus the complex nature of technologies. Complex technologies embed many different patented inventions in one final product, such that firms in complex industries adopt an aggressive filing strategy. A recent paper by von Graevenitz *et al.* (2011) provides a measure of complexity by industry. The authors constructed a measure of patent thickets by technology area based on "triples" of firms that mutually block some of each others' patents. They defined the most complex technology areas as those with the highest density of triples, as estimated from European patent citations data. We use the variable "COMPLEXITY" to capture differences in filing strategies across industries.[11]

As there might be important differences in the propensity to patent across countries, the econometric analysis also controls for two country-level variables. "IP INDEX" is a measure of the strength of the intellectual property (IP) system. It was developed by Ginarte and Park (1997) and updated by Park (2008). Countries with stronger IP regimes are expected to have a higher propensity to patent, as a strong protection increases the value of patent rights and signals a more advanced patent system.[12] However, the variable is an imperfect proxy, as it is only computed every five years and is relatively stable over time.[13] "QUALITY" is a cross-country index of the quality of patent systems calculated by de Saint-Georges and van Pottelsberghe (2012). It measures the stringency and transparency of patent selection mechanisms. High-quality patent systems, defined as patent systems that prevent strategic games and abusive behaviors, should have a lower number of patents. These two variables might affect not only the filing strategy but also the appropriability strategy. For instance, a high-quality patent system may simultaneously discourage the strategic filing of minor improvements in existing technologies and increase the economic returns of patent protection, thereby increasing the incentives to apply for patents.

4. Empirical results

The empirical results are presented and interpreted in two stages. In the first stage, we present the results of the econometric regression. We start by estimating a basic R&D-patent model with the five patent indicators. We then introduce the productivity and the propensity variables to the regression model. In the second stage, we decompose the sources of growth in patenting activity. We perform a semi-partial R^2 decomposition of the regression results

[11] We thank von Graevenitz *et al.* for providing a time series of the variable.

[12] van Pottelsberghe (2011) argues that Ginarte and Park's index is not so much an index of the strength of patent rights as a measure of the applicant-friendliness of the patent system. Both of these dimensions are likely to increase the strategic propensity.

[13] To avoid losing too many data points, we compute annual data on the basis of the compound annual growth rate.

and we provide an in-depth analysis of the fixed effects (industry, country, and time dummies).

4.1. Econometric estimates

The basic R&D-patent model

The estimated parameters of the error correction model described in equation (6) are presented in Table 5 for the five patent indicators. The only explanatory variable taken into account is the stock of R&D expenditure.

Table 5. Results of the error-correction model of the R&D-patent relationship

Δ log(#patents)	**NPFCORR**	**TRIADIC**	**EPO**	**USPTO**	**REGIONAL**
	(1)	(2)	(3)	(4)	(5)
Δ log(R&D STOCK)	0.100***	0.111	0.095**	0.022	0.092**
	(0.026)	(0.070)	(0.040)	(0.060)	(0.040)
log(#patents) (t-1)	-0.118***	-0.293***	-0.157***	-0.144***	-0.151***
	(0.013)	(0.031)	(0.019)	(0.018)	(0.019)
log(R&D STOCK) (t-1)	0.015***	0.036***	0.021***	0.018***	0.022***
	(0.002)	(0.006)	(0.003)	(0.003)	(0.003)
Country dummies	Yes ***	Yes ***	Yes ***	Yes ***	Yes ***
Industry dummies	Yes ***	Yes ***	Yes ***	Yes ***	Yes ***
Time dummies	Yes ***	Yes ***	Yes ***	Yes ***	Yes ***
Number of observations	5,143	5,143	5,143	5,143	5,143
Adjusted R-Squared	0.187	0.188	0.155	0.174	0.129
Long-run impact of R&D	0.126***	0.123***	0.133***	0.127***	0.142***
	(0.018)	(0.018)	(0.016)	(0.023)	(0.017)

Notes: Robust standard errors in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The rows “country dummies,” “industry dummies,” and “time dummies” report the significance levels of the joint effect of these dummies.

The short-term elasticity of patents with respect to R&D stock is about 0.10, while the long-term elasticity of R&D stock is around 0.12, as indicated in the bottom rows of Table 3. Two remarks must be made regarding these estimated long-term elasticities. First, although the various point estimates are strikingly low, they are compatible with estimates performed at the industry level by Meliciani (2000).[14] Second, the elasticity is stable across patent counts, suggesting some degree of comparability between studies that use different patent indicators. This stability is all the more remarkable given the notable variations in the adjustment parameters (coefficients associated with the variable 'log(R&D STOCK) (t-1)') and the strong variations in patent counts illustrated in Figure 1.

Depending on the patent indicator used, the regression model explains between 12% and 14% of the growth in patent applications. The explanatory power is fairly high despite the nature of the data and the simplicity of the patent production function. Country, industry, and time effects are all jointly significant. They are described and analyzed in the second stage of the empirical analysis. Note that the tests for autocorrelation of residuals reject the presence of correlated errors.

Productivity and propensity variables

The low estimated elasticity of patents with respect to R&D raises the question of whether other factors may help to explain variations in patent applications. This issue is investigated in Table 6, where the productivity and propensity components are both included in the model. For the sake of readability, the estimations are presented only with the NPFCORR, TRIADIC, and REGIONAL patent indicators as dependent variables. Regressions based on EPO and USPTO lead to similar results.

[14] The low elasticity is also robust to changes in model specifications: ECM with R&D flows; IV estimation using past values of R&D as instruments; and within transformation of equation (4). The results are available upon request.

Table 6. Results of the full error-correction model

Δ log(#patents)	**NPFCORR**	**TRIADIC**	**REGIONAL**
	(1)	(2)	(3)
Δ log(Stock R&D)	0.036	0.010	-0.016
	(0.035)	(0.086)	(0.045)
Δ SHARE HIGHER EDU	-0.009***	-0.001	-0.008***
	(0.002)	(0.004)	(0.002)
Δ RCA	-0.022	0.039	-0.044
	(0.021)	(0.060)	(0.037)
log(#patents) (t-1)	-0.149***	-0.286***	-0.145***
	(0.019)	(0.035)	(0.022)
log(Stock R&D) (t-1)	0.013***	0.016***	0.009***
	(0.003)	(0.006)	(0.003)
SHARE HIGHER EDU (t-1)	0.0001	-0.002	0.005***
	(0.001)	(0.002)	(0.001)
RCA (t-1)	0.020***	0.043***	0.026***
	(0.004)	(0.009)	(0.005)
APPROPRIABILITY	0.004***	0.012***	0.005***
	(0.001)	(0.002)	(0.001)
Δ COMPLEXITY	-0.0004	-0.001	-0.0001
	(0.0003)	(0.001)	(0.0004)
COMPLEXITY (t-1)	0.0001	0.001*	0.001**
	(0.0002)	(0.0004)	(0.0003)
IP INDEX	0.031**	0.056**	0.075***
	(0.016)	(0.023)	(0.019)
QUALITY	-0.008***	-0.007***	-0.007***
	(0.001)	(0.001)	(0.001)
Country dummies	Yes ***	Yes ***	Yes ***
Industry dummies	Yes ***	Yes ***	Yes ***
Time dummies	Yes ***	Yes ***	Yes ***
Number of observations	3,704	3,704	3,704
Adjusted R-Squared	0.235	0.190	0.143
Long-run impact of R&D	0.088***	0.055***	0.063***
	(0.018)	(0.02)	(0.02)
Long-run impact of SHARE HIGHER EDU	0.001	-0.008	0.036***
	(0.005)	(-0.006)	(0.009)
Long-run impact of RCA	0.135***	0.151***	0.180***
	(0.03)	(0.029)	(0.032)
Long-run impact of COMPLEXITY	0.001	0.002*	0.004**
	(0.001)	(0.001)	(0.002)

Notes: Robust standard errors in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The rows "country dummies," "industry dummies," and "time dummies" report the significance levels of the joint effect of these dummies.

Productivity variables – The three indicators that are likely to be correlated with research productivity are higher education's share of total R&D expenditure, basic research's share of total R&D expenditure, and an indicator of international comparative advantage. The first two indicators vary across countries and over time, while the third fluctuates in all three dimensions. The share of total R&D performed by the higher education sector (SHARE HIGHER EDU) only has a positive and significant impact on the regional patent indicator, suggesting that university-performed R&D leads to more valuable patents in the long run.[15] The negative short-term impact of this variable is probably due to a transitional effect caused by the diversion of resources towards institutions that are less patent minded. It can also be explained by the likelihood that R&D processes are more drawn out in universities than in the private sector.

The share of basic research, which serves as an indicator of the relative efforts directed at potential breakthrough inventions, is tested separately. It is not included in the main specification due to the high amount of missing information. The results are presented in Table A5 of Appendix 1. The share of basic research has a strong productivity effect on all patent indicators, with long-term elasticity of 0.08 to 0.17. In other words, the higher the share of basic research in total R&D expenditure, the higher the number of patent applications induced by an increase in research productivity. This confirms that the allocation of more resources to basic research can be adopted as a long-term policy aimed at securing future innovation.

Revealed comparative advantage (RCA) has a positive and significant impact on the number of patent filings in the long run. This result confirms the impact on research productivity that Furman *et al.* (2002) estimate with their variable OPENNESS. Note that the effect is higher with international patents than with priority filings, which indicates a correlation between international competitiveness and international patenting activity. Interestingly, the long-term elasticity of patents with respect to R&D drops substantially when productivity variables are added to the model. The decline is most severe for high-value patents, which underscores the importance of productivity effects for these patents.

[15] A positive effect was also expected with triadic filings. However, this is not observed, probably due to the budgetary constraints for higher education institutions, which are not endowed to file simultaneously at the three main regional patent offices.

Propensity variables – Empirically implementing the distinction between appropriability strategies and filing strategies made in the present paper is not straightforward. The four proxies that are used to gauge these effects are imperfect measures because they vary only across countries or across industries, and because they are quite stable over time. Despite these limitations, the share of inventions patented (APPROPRIABILITY) is highly significant, which provides evidence that the appropriability strategy plays a key role in the R&D-patent relationship, especially for high-value triadic patents.

The variable that aims to capture the filing strategy is the measure of complexity (COMPLEXITY). Industries in which complexity has increased have seen a rise in patent filings. The fact that the variable correlates with the regional and triadic indicators suggests that filing strategies are office specific (indeed, the complexity measure is built using "regional" EPO data). This result illustrates the need to collect such data on a more systematic basis. The variables IP INDEX and QUALITY measure various dimensions of the design of patent systems. Both variables are significant determinants of the number of patents. Countries with a high IP index are applicant friendly and, hence, likely to have a high number of patent filings per unit of R&D. For instance, the US has a very high IP index because there are many patentable subject matters (as opposed to Europe, where many restrictions apply), and because the enforcement system is well developed and historically supportive of patent holders. The opposite holds for the quality variable: countries which score high on QUALITY – those that prevent strategic patenting through a higher degree of transparency and more stringency – tend to have a lower number of patent applications, suggesting that the design of patent systems significantly influences filing strategies.

4.2. Decomposition of the sources of growth in patenting activity

The second stage of the empirical analysis involves decomposing the sources of growth in patenting activity. We provide a variance decomposition of the patent growth as well as an in-depth analysis of the fixed effects included in the ECM.

Variance decomposition: semi-partial R^2 analysis

A semi-partial R^2 analysis measures to extent to which a regressor uniquely contributes to explaining the variance in the dependent variable. It involves computing the difference between the R^2 of the model estimated with all the variables of interest (henceforth, R^2 full) and the R^2 of the model excluding the focal regressor(s). The decomposition of R^2 full is presented in Table 7, for the three patent indicators. Note that the semi-partial R^2 are expressed as a percentage of R^2 full for ease of comparability.

Table 7. Semi-partial R^2 analysis of the ECM

Specification	*R^2 full*	Semi-Partial R^2 (% of R^2 full)				
		R&D stock	Control variables	Country dummies	Industry dummies	Year dummies
NPFCORR						
Full model	0.2474	1.36	5.68	49.48	18.80	23.80
Average country	0.7121	1.85	2.49	-	14.86	37.54
Average industry	0.3553	3.08	7.87	49.44	-	22.01
Average year	0.6320	0.86	2.53	44.42	9.78	-
TRIADIC						
Full model	0.2030	0.71	5.11	56.25	37.28	17.95
Average country	0.7243	1.72	3.07	-	24.19	32.55
Average industry	0.3707	4.90	8.60	54.00	-	20.02
Average year	0.5448	1.98	2.91	41.11	17.10	-
REGIONAL						
Full model	0.1566	0.98	14.69	41.25	24.92	18.81
Average country	0.6780	1.57	3.81	-	25.57	32.89
Average industry	0.3234	4.79	19.27	47.46	-	23.07
Average year	0.4774	1.68	5.71	37.22	15.52	-

Notes: R^2 and semi-partial R^2 are computed based on the econometric results of Table 6. The rows 'Average country', 'Average industry' and 'Average year' present the average of the estimations performed for each individual country, each industry and each year, respectively.

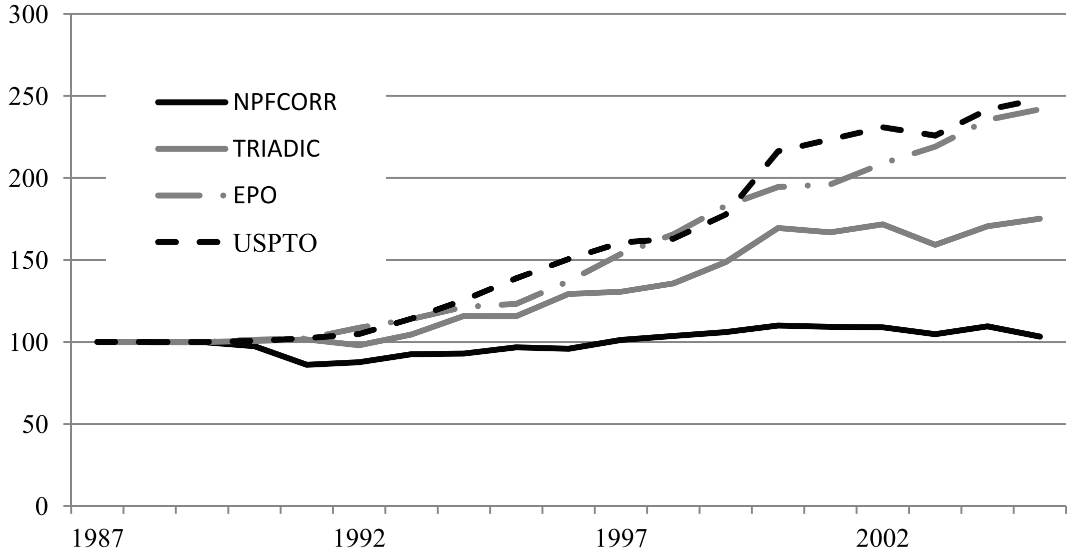
Four observations are particularly noteworthy. First, R&D stock only accounts for a small share of variance explained (from 1 to 5 per cent according to the model specifications). This result illustrates that patent indicators do not merely reflect research intensity but also other aspects of the innovation process such as the productivity and the propensity dimensions. The low contribution of R&D must nevertheless be tempered by the very constraining econometric approach adopted. The study of the growth rates of patent numbers, as opposed to their levels, reduces the contribution of R&D to patenting activity. This observation applies to all the variables though. Second, although the productivity and the propensity variables imperfectly capture the productivity and the propensity components, the control variables taken together explain more than R&D stock. Third, country, industry, and year effects account for the largest proportion of variance explained. In particular, it is shown that country dummies capture more variance in patenting activities than industry dummies. This observation is particularly true for priority filings (NPFCORR) but also for triadic and regional patents to a lesser extent, highlighting the importance of national innovation systems in explaining innovation performances. Finally, a large share of the variance remains unexplained, indicating the importance of idiosyncratic components in the R&D-patent relationship.

Time, country, and industry effects

Since the fixed effects included in our econometric model capture a large share of variance in patent growth, it is particularly interesting to analyze them in greater detail. Indeed, the time, country, and industry effects from the full model can be used to assess the average evolution of patent numbers along the three dimensions (see Appendix 3 for methodological details). As the model explains the growth rate of patent filings, the dummies capture the increase in patents net of the impact of all other observable characteristics. As explained in section 3, the fixed effects capture unobserved changes in productivity and in the propensity to patent. Looking at each effect separately provides a deeper understanding of the nature of the increase in patenting activity. In particular, the variation of the fixed effects across patent indicators is particularly worth looking at.

Figure 2 depicts the growth of patents over time for the main patent indicators. It represents the cumulative time effects, net of the average industry and country effects. The most striking observation is that the propensity to file priority filings has been roughly constant over time, whereas the propensity to file international/regional applications has steadily increased. This result leads to two important conclusions. First, there has been no particular “spurt” in underlying inventiveness (beyond the increase in R&D efforts and the improvement in research productivity caputred in the empirical analysis). Second, the “patent warming” observed at major patent offices is driven by a globalization phenomenon – companies are not producing more patents, but they are extending them abroad more frequently.

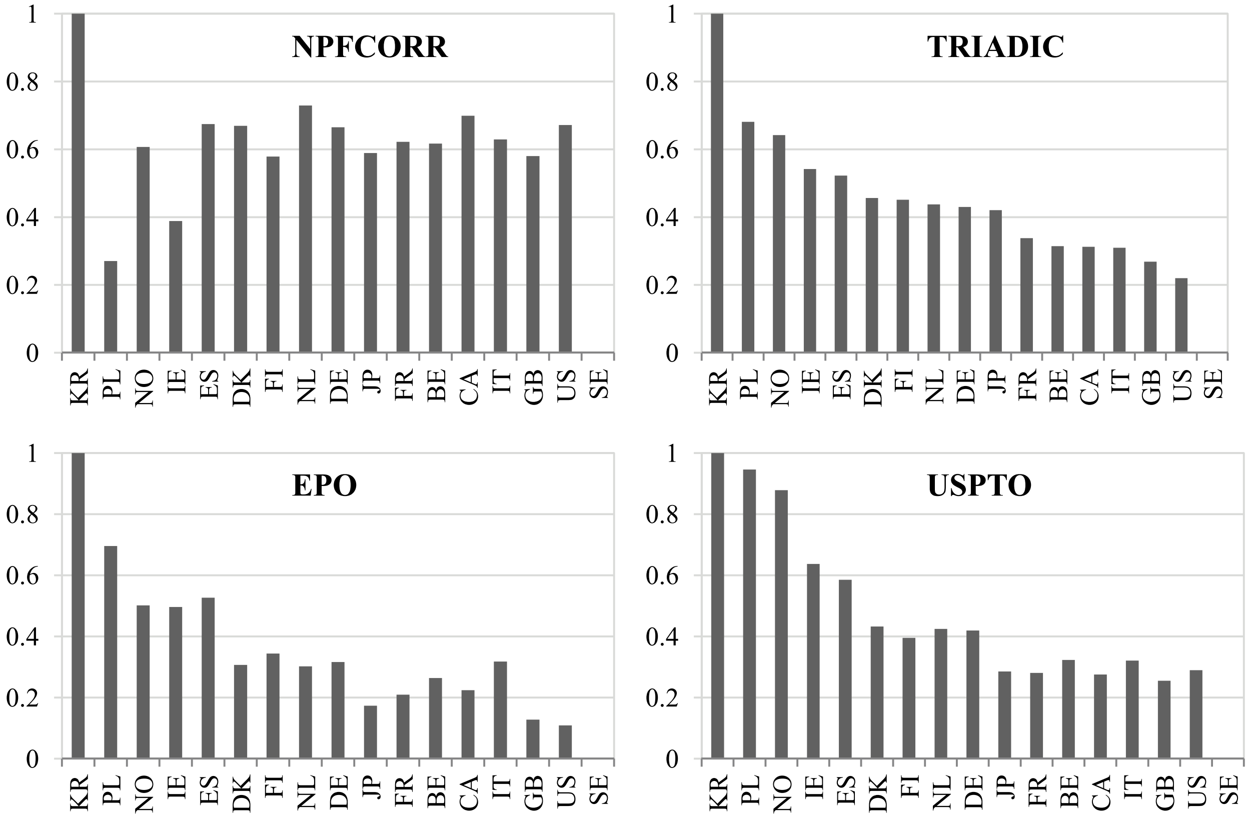
Figure 2. Time effects



Source: Own calculations (see Appendix 3 for more details)

Figure 3 shows the normalized parameters associated with the country dummies. The rankings for the international indicators (TRIADIC, EPO, and USPTO) are roughly similar and clearly underline a strong catch-up effect for South Korea, Poland, Norway, Ireland, and Spain. Countries such as France, Canada, the United Kingdom, and the US rank last on triadic and regional patent statistics (EPO and USPTO), suggesting that they have lost some ground in their patenting performance as measured by international indicators. Interestingly, the ranking for NPFCORR is almost the reverse, with Poland ranking among the lowest and the US among the highest (Korea being a notable exception). This suggests that catch-up countries have not necessarily improved their research productivity bur rather increased their presence on the international patent scene.

Figure 3. Country effects

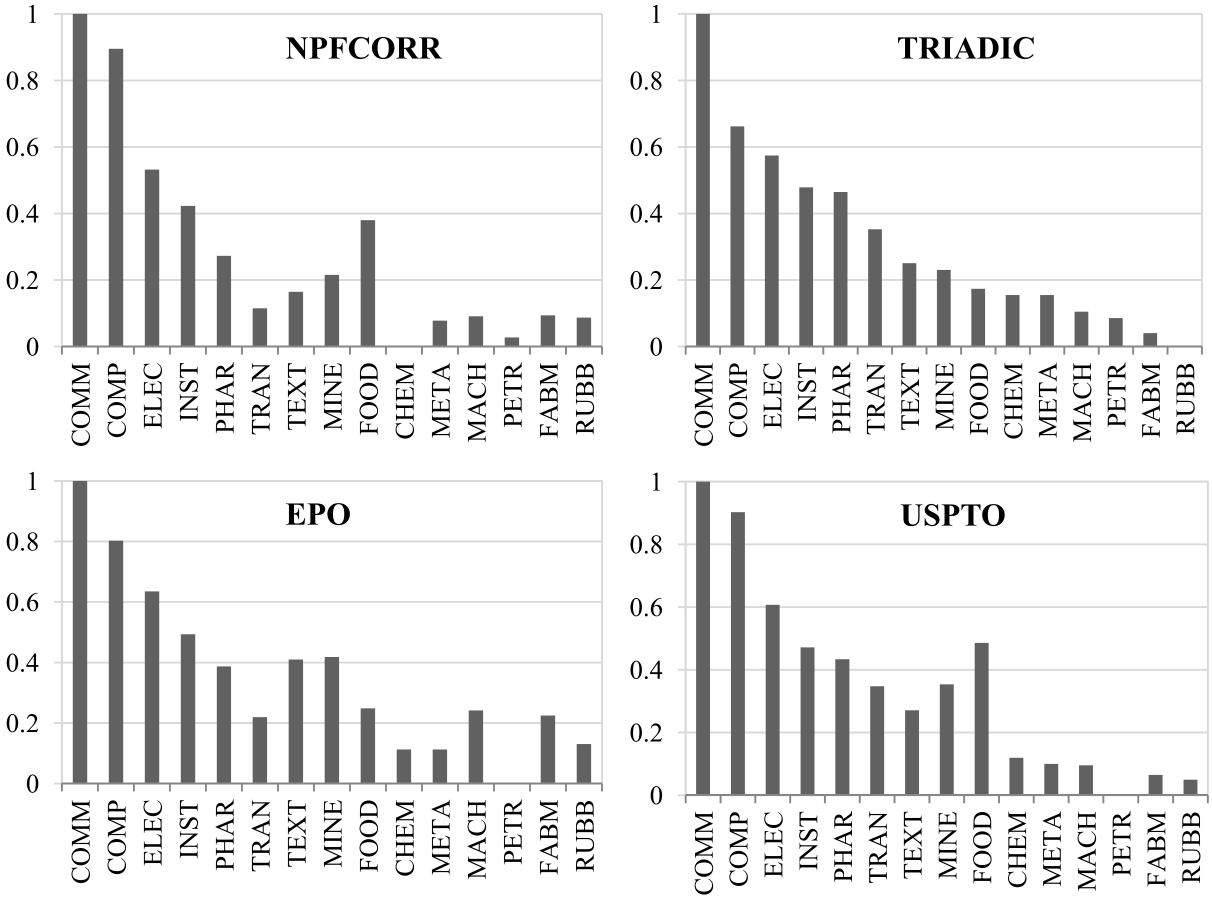


Source: Own calculations

Notes: The values are coefficients of country dummies taken from the full model and are normalized from 0 to 1. See Appendix 3 for more details.

The industry-specific growth in patents also exhibits strong variability, as illustrated in Figure 4. The industries related to communication, computers, and instruments are associated with the strongest increase in the propensity to patent, whereas fabricated metals, and rubber and plastics products have the lowest increase. There is a clear ICT (information and communication technologies) effect at play. Industries in this area scored high in at least one of the two propensity components and they have apparently further increased their willingness to patent. This observation is true for all patent indicators. Contrary to the country dummies, which illustrate a catch-up effect among newcomers, the increase in patent filings is visible in industries that make great use of strategic patenting, suggesting that most of the growth in these industries is driven by an increase in the propensity to patent.

Figure 4. Industry effects



Source: Own calculations

Notes: The values are coefficients of industry dummies taken from the full model and are normalized from 0 to 1. See Appendix 3 for more details.

5. Concluding remarks and policy implications

This paper sheds light on the origins of the worldwide growth in patenting activity. The empirical investigation relies on a unique panel dataset composed of 18 manufacturing industries in 19 countries covering the period from 1987 to 2005, for which five broad patent indicators are developed. The paper has six main methodological and policy implications.

The first contribution is conceptual. The literature has implicitly or explicitly assumed that the patent-to-R&D ratio is driven by a research productivity effect (the extent to which additional units of R&D generate additional inventions) and a propensity-to-patent effect. The variance decomposition confirms the importance of these effects, which account for a significant share of the variance in the growth in patenting activity. This paper claims that a distinction between two main components of the propensity to patent improves our understanding of the R&D-patent relationship. These two components are the "appropriability strategy," which indicates whether an invention is protected by a patent, and the "filing strategy," which measures the number of patents used to protect an innovation. While the former component can be proxied by existing survey data on the share of inventions that are patented in each industrial sector (e.g., Arundel and Kabla, 1998), the latter can, thus far, only be gauged using measures of complexity. This theoretical insight has a major implication: large-scale surveys, such as the Community Innovation Survey in Europe, should assess the two propensity components on a regular basis. Data on the evolution of the share of inventions that are patented as well as on the average number of patents that are used to protect an innovation would drastically improve our understanding of patent indicators.

Second, the econometric analysis of patenting activity across industries and countries, and over time confirms that the long-term elasticity of patents with respect to R&D stock is positive and significant, but small. It fluctuates at around 12% and is remarkably stable across patent indicators (from the all-encompassing national priority filings to the more restrictive, high-value triadic patents). However, the elasticity is much smaller than "hoped" for (Griliches, 1990) and R&D explains only a small share of the variance in patent filings.

Third, the empirical analysis confirms the presence of a significant productivity effect, which explains part of the variance in the R&D-patent ratio, as demonstrated by the positive and significant premium associated with basic research and academic research, or by the noticeable impact of the revealed comparative advantage variable, which is an indicator of ultimate innovation performance. The positive impact of basic and academic research also suggests that allocating more resources to university-performed research and to basic projects can form the basis for a long-term policy aimed at securing future innovation.

Fourth, the appropriability variable plays a positive, highly significant, role in the patent production function, even though it only varies across industries. The filing strategy is assessed using a measure of the complexity of industries. The variable has a positive and significant impact on the propensity to patent, but probably captures only one facet of the filing strategy. The design of the patent system also plays a notable role in patent strategies; both the strength – or the applicant friendliness – of the patent system and its quality (stringency and transparency) affect the number of patent applications.

Fifth, the country and industry dummies allow for some in-depth identification of the origins of the patent explosion. Two manufacturing industries that were already characterized by a high patent-to-R&D ratio – communications and computers – are associated with the sharpest increase in patenting activity. This is precisely the technological area in which a "patent paradox" was identified by Hall and Ziedonis (2001). In this respect, our results shed some additional light on the R&D-patent relationship and its industry dimension. The pharmaceutical industry has a high appropriability strategy but the associated industry dummy suggests a relatively stable propensity to patent. The countries that are associated with the sharpest increase in patenting activities are South Korea, Poland, and Spain, which suggests a clear catch-up effect. These results exemplify the pitfalls and advantages associated with patent data. Whereas such data highlight fundamental economic changes, such as catch-up effects, they are also greatly impacted by national industrial structures. This finding, therefore, stresses the need to improve our understanding of the "propensity" components.

Finally, the time dummies provide a broad measure of the increase in patenting activity, net of country and industry specificities, and net of R&D expenditure and other control variables. Here the results depend on the patent indicators that are used. The sharpest increases are associated with regional patent filings (at the EPO or at the USPTO) followed by triadic applications. As far as national priority filings are concerned, hardly any increase is observed. In other words, the "global patent warming" that is currently underway is essentially the result of the internationalization of patent applications and not a consequence of increased research productivity. Innovative firms are increasingly targeting global markets and hence have a higher tendency to seek protection in key markets worldwide. This tendency would justify the closer coordination of patent offices at the global level, provided that their views on patent system design converge.

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Appendix 1. Additional background tables

Table A1. Literature on the R&D-patent relationship

Reference	Sample	Model	Results	Specifications
Firm Level				
Pakes and Griliches (1980)	121 US firms 1968-1875 (USPTO)	Panel (within dimension)	0.61***	Sum of log R&D (contemporaneous + 5 lags)
Bound *et al.* (1984)	2,582 US firms 1976 (USPTO)	Cross section; OLS	0.32-0.38***	
		Cross section; poisson, negative binomial, and non-linear least squares	0.58-2.18***	
Hausman *et al.* (1984)	128 US firms 1968-1974 (USPTO)	OLS, poisson, and negative Binomial	0.57-0.88***	Sum of log R&D (contemporaneous + 5 lags)
		Poisson and negative binomial with firm effects	0.35-0.6***	Sum of log R&D (contemporaneous + 5 lags)
		Poisson and negative binomial "between" firms	0.75-1.29***	Contemporaneous log R&D
Hall *et al.* (1986)	642 US manufacturing firms 1972-1979 (USPTO)	Non-linear least squares, poisson, negative binomial and GMT	0.39-0.66***	Sum of log R&D (contemporaneous + 3-7 lags)
		Conditional negative binomial and GMT with firm effects	0.29-0.38***	Sum of log R&D (contemporaneous + 3-5 lags)
Jaffe (1986)	432 US firms 1973 and 1979 (USPTO)	Cross section; pooled OLS	0.74***	Contemporaneous log R&D
		First differences	0.4*	
		3SLS	0.88***	
Cincera (1997)	181 international manufacturing firms 1983-1991 (EPO)	Panel; GEC, QGPML-gamma, conditional poisson and GMM	0.35-0.9***	Sum of log of R&D (contemporaneous + 4 lags)
Duguet and Kabla (1998)	299 FR firms 1990-1992 (EPO)	Cross-section; poisson model estimated by asymptotic least squares	0.34-0.67***	Log R&D
Crépon *et al.* (1998)	4164 FR manufacturing firms 1986-1990 (EPO)	Cross-section; non-negative binomial	0.88-1.08***	Patents per employee and R&D capital per employee
Blundell *et al.* (2002)	407 US firms 1972-1979 (USPTO)	Linear feedback model	0.9***	Level (without individual effects)
			0.34***	Within-group mean scaling
Arora *et al.* (2008)	790 US manufacturing R&D Units 1991-1993	Cross section; 2SLS	0.61***	
Czarnitzki *et al.* (2009)	122 BE firms 1993-2003 (EPO)	Pooled cross sectional	0.52-0.6***	Log(R&D/employment)
		Fixed effect panel	0.28-0.3***	Log(R&D/employment)
Aggregate (industry, region, or country) level				
Acs and Audretsch (1988)	247 US manufacturing industries	Cross section	0.36***	Log (innovations)1982 and log(total R&D)1977
			0.41***	Log (innovations)1982 and log(company R&D)1977
Meliciani (2000)	Panel of 15 industrial sectors, 12 OECD countries, 1973-1993 (USPTO)	Negative binomial	0.18***	With country and sector effects
			0-0.56***	Regressions by sector (with country effects)
Botazzi and Peri (2003)	86 European regions 1977-1995 (EPO)	Cross section of long run-averages	0.76-0.95**	Patent and R&D per square kilometer
Bottazzi and Peri (2007)	15 OECD countries 1973-1999	Long-run cointegration relation; DOLS	0.30-0.79***	International patent applications

	(USPTO)			
de Rassenfosse and van Pottelsberghe (2009)	34 countries 2003 (USPTO, EPO, TRIAD, PF)	Cross section	0.33-1.56***	Log researchers

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A2. Abbreviations of countries and industries

Abbr.	Country	Abbr.	ISIC Rev.3	Industry definition	Technological classification*	Complexity**
AT	Austria	**FOOD**	15-16	Manufacture of food products, beverages, and tobacco products	LOTE	0
BE	Belgium	**TEXT**	17-19	Manufacture of textiles and apparel; dressing and dyeing of fur; tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harnesses, and footwear	LOTE	4
CA	Canada	**WPAP**	20-22	Manufacture of wood and products made of wood and cork, except furniture; manufacture of articles made of straw and plaiting materials; manufacture of paper and paper products; publishing, printing, and reproduction of recorded media	LOTE	13
CH	Switzerland	**PETR**	23	Manufacture of coke, refined petroleum products, and nuclear fuel	MLTE	6
DE	Germany	**CHEM**	24 less 2423	Manufacture of chemicals and chemical products	MHTE	6
DK	Denmark	**PHAR**	2423	Pharmaceuticals and medicinal chemicals	HTE	4
ES	Spain	**RUBB**	25	Manufacture of rubber and plastics products	MLTE	15
FI	Finland	**MINE**	26	Manufacture of other non-metallic mineral products	MLTE	2
FR	France	**META**	27	Manufacture of basic metals	MLTE	2
GB	United Kingdom	**FABM**	28	Manufacture of fabricated metal products, except machinery and equipment	MLTE	2
IE	Ireland	**MACH**	29	Manufacture of machinery and equipment n.e.c.	MHTE	2
IT	Italy	**COMP**	30	Manufacture of office, accounting, and computing machinery	HTE	55
JP	Japan	**ELEC**	31	Manufacture of electrical machinery and apparatus n.e.c.	MHTE	24
KR	Korea	**COMM**	32	Manufacture of radio, television, and communication equipment and apparatus	HTE	99
NL	Netherlands	**INST**	33	Manufacture of medical, precision, and optical instruments, and watches and clocks	HTE	22
NO	Norway	**AUTO**	34	Manufacture of motor vehicles, trailers, and semi-trailers	MHTE	21
PL	Poland	**TRAN**	35	Manufacture of other transport equipment	MHTE	21
SE	Sweden	**MISC**	36	Manufacture of furniture; manufacturing n.e.c.	LOTE	
US	United States					

Notes: * Based on the OECD technological classifications. LOTE, MLTE, MHTE, and HTE stand for low technology, medium-low technology, medium-high technology, and high technology, respectively. ** Own industry matching based on the average of "triples" data across time, as presented by von Graevenitz *et al.* (2011).

Table A3. Absolute and relative number of patents by country

COUNTRY	NPFCORR			EPO			TRIADIC			USPTO			REGIONAL		
	Y05	%	CAGR	Y05	%	CAGR	Y05	%	CAGR	Y05	%	CAGR	Y05	%	CAGR
AT	2485	0.7	2.9%	1345	1.3	4.6%	304	0.6	2.9%	886	0.4	5.2%	1345	0.6	4.6%
BE	1803	0.5	3.5%	1283	1.2	5.4%	398	0.8	3.9%	939	0.4	5.9%	1283	0.6	5.4%
CA	6040	1.6	4.2%	1198	1.2	4.1%	384	0.8	0.5%	3909	1.8	4.7%	3909	1.7	4.7%
CH	3599	1.0	0.8%	2738	2.6	2.5%	1029	2.1	0.7%	1938	0.9	2.1%	2738	1.2	2.5%
DE	49150	13.3	3.4%	24529	23.6	4.9%	6994	14.1	2.7%	17422	8.0	4.8%	24529	10.6	4.9%
DK	1545	0.4	2.1%	1021	1.0	8.3%	319	0.6	6.5%	920	0.4	8.6%	1021	0.4	8.3%
ES	2657	0.7	2.8%	988	1.0	10.6%	198	0.4	8.2%	581	0.3	8.6%	988	0.4	10.6%
FI	2535	0.7	1.8%	1069	1.0	7.7%	291	0.6	5.2%	1078	0.5	7.4%	1069	0.5	7.7%
FR	14789	4.0	1.4%	7904	7.6	3.3%	2677	5.4	2.3%	5577	2.6	3.6%	7904	3.4	3.3%
GB	18708	5.1	0.2%	5159	5.0	1.6%	1937	3.9	1.0%	5768	2.7	3.5%	5159	2.2	1.6%
IE	610	0.2	-5.1%	255	0.2	7.1%	88	0.2	7.1%	291	0.1	8.5%	255	0.1	7.1%
IT	10334	2.8	1.9%	4279	4.1	5.1%	754	1.5	1.4%	2373	1.1	3.7%	4279	1.9	5.1%
JP*	112715	30.6	0.6%	23693	22.8	3.0%	18554	37.4	5.0%	52932	24.3	3.7%	52932	22.9	3.7%
KR*	33980	9.2	22.0%	5255	5.1	37.0%	3145	6.3	38.2%	18424	8.5	28.9%	18424	8.0	28.9%
NL	5560	1.5	5.0%	3631	3.5	5.5%	2149	4.3	6.0%	3139	1.4	6.3%	3631	1.6	5.5%
NO	1295	0.4	2.2%	436	0.4	8.0%	157	0.3	6.2%	501	0.2	7.8%	436	0.2	8.0%
PL	866	0.2	-9.8%	122	0.1	9.2%	12	0.0	6.4%	91	0.0	11.5%	122	0.1	9.2%
SE	2831	0.8	-1.7%	1825	1.8	4.1%	694	1.4	3.2%	1500	0.7	3.7%	1825	0.8	4.1%
US	96935	26.3	4.4%	17292	16.6	1.5%	9587	19.3	-0.8%	99274	45.6	4.8%	99274	43.0	4.8%
TOTAL	368436	100.0	2.5%	104021	100.0	3.7%	49670	100.0	2.8%	217543	100.0	4.9%	231123	100.0	4.8%

Source: Own calculations

Notes: * The number of priority fillings for Japan and Korea has been divided by 3. The columns labeled ‘Y05’ report the total patent count per country in the year 2005, the columns labeled ‘%’ report the share of each country in the total of each patent count for the year 2005, expressed as percentages, and the columns labeled ‘CAGR’ report the compound annual growth rate of each patent count indicator over the largest available period.

Table A4. Absolute and relative number of patents by industry

INDUSTRY	NPFCORR			EPO			TRIADIC			USPTO			REGIONAL		
	Y05	**%**	**CAGR**	**Y05**	**%**	**CAGR**	**Y05**	**%**	**CAGR**	**Y05**	**%**	**CAGR**	**Y05**	**%**	**CAGR**
FOOD	7625	2.1	2.0%	2131	2.0	2.5%	955	1.9	1.0%	3995	1.8	3.2%	4108	1.8	3.0%
TEXT	2441	0.7	2.3%	622	0.6	3.2%	269	0.5	2.1%	1269	0.6	4.0%	1383	0.6	4.0%
WPAP	4550	1.2	1.7%	1325	1.3	2.9%	594	1.2	1.9%	2366	1.1	3.4%	2606	1.1	3.5%
PETR	4476	1.2	0.6%	1499	1.4	1.1%	737	1.5	0.2%	2502	1.2	1.9%	2678	1.2	1.9%
CHEM	36016	9.8	1.1%	12317	11.8	1.7%	6253	12.6	0.8%	20196	9.3	2.6%	21895	9.5	2.6%
PHAR	20427	5.5	1.7%	8779	8.4	2.3%	4858	9.8	1.2%	13425	6.2	3.3%	14357	6.2	3.2%
RUBB	7058	1.9	1.8%	2021	1.9	2.9%	822	1.7	1.8%	3300	1.5	3.0%	3781	1.6	3.2%
MINE	6537	1.8	1.5%	1824	1.8	2.7%	825	1.7	1.9%	3517	1.6	3.9%	3846	1.7	3.8%
META	7565	2.1	0.7%	2154	2.1	2.2%	993	2.0	1.5%	3962	1.8	3.0%	4342	1.9	3.1%
FABM	9794	2.7	1.9%	2576	2.5	3.6%	904	1.8	2.5%	4352	2.0	3.3%	5078	2.2	3.5%
MACH	43844	11.9	1.5%	11991	11.5	3.6%	4692	9.4	2.5%	22165	10.2	3.8%	24630	10.7	3.9%
COMP	53685	14.6	3.5%	12589	12.1	4.7%	6698	13.5	4.1%	36124	16.6	7.1%	36745	15.9	6.9%
ELEC	14118	3.8	2.9%	3774	3.6	4.7%	1790	3.6	4.0%	8640	4.0	6.0%	9143	4.0	5.9%
COMM	82057	22.3	3.8%	21827	21.0	5.6%	11330	22.8	4.9%	55830	25.7	7.3%	57167	24.7	7.1%
INST	15047	4.1	2.4%	4152	4.0	3.8%	2082	4.2	3.1%	9202	4.2	4.9%	9633	4.2	4.9%
AUTO	33411	9.1	2.7%	9832	9.5	5.0%	4010	8.1	3.9%	16580	7.6	4.4%	18712	8.1	4.7%
TRAN	10551	2.9	1.8%	3084	3.0	3.7%	1308	2.6	2.8%	5861	2.7	4.0%	6410	2.8	4.1%
MISC	9235	2.5	3.3%	1523	1.5	3.8%	551	1.1	3.3%	4256	2.0	4.1%	4607	2.0	4.1%
TOTAL	368436	100.0	2.5%	104021	100.0	3.7%	49670	100.0	2.8%	217543	100.0	4.9%	231123	100.0	4.8%

Source: Own calculations

Notes: The columns labeled ‘Y05’ report the total patent count per industry in the year 2005, the columns labeled ‘%’ report the share of each industry in the total of each patent count for the year 2005, expressed as percentages, and the columns labeled ‘CAGR’ report the compound annual growth rate of each patent count indicator over the largest available period.

Table A5. Partial model with share of basic research in total R&D

Δ log(#patents)	NPFCORR		TRIADIC		REGIONAL	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ log(Stock R&D)	0.110**	0.132***	0.045	0.085	0.074	0.108
	(0.048)	(0.048)	(0.131)	(0.138)	(0.084)	(0.086)
Δ SHARE BASIC		0.016***		-0.0001		-0.005
		(0.004)		(0.009)		(0.007)
log(#patents) (t-1)	-0.135***	-0.111***	-0.364***	-0.368***	-0.180***	-0.193***
	(0.017)	(0.017)	(0.050)	(0.050)	(0.037)	(0.038)
log(Stock R&D) (t-1)	0.020***	0.014***	0.040***	0.037***	0.026***	0.025***
	(0.004)	(0.003)	(0.010)	(0.009)	(0.006)	(0.006)
SHARE BASIC (t-1)		0.019***		0.028***		0.023***
		(0.003)		(0.005)		(0.004)
Country dummies	Yes ***	Yes ***	Yes ***	Yes ***	Yes ***	Yes ***
Industry dummies	Yes ***	Yes ***	Yes ***	Yes ***	Yes ***	Yes ***
Time dummies	Yes ***	Yes ***	Yes ***	Yes ***	Yes ***	Yes ***
Number of observations	1,812	1,812	1,812	1,812	1,812	1,812
Adjusted R-Squared	0.303	0.327	0.231	0.241	0.149	0.171
Long-run impact of R&D	0.147***	0.129***	0.11***	0.101***	0.144***	0.13***
	(0.024)	(0.027)	(0.024)	(0.023)	(0.028)	(0.027)
Long-run impact of SHARE BASIC		0.171***		0.076***		0.119***
		(0.029)		(0.015)		(0.019)

Notes: Robust standard are errors in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The rows “country dummies,” “industry dummies,” and “time dummies” report the significance levels of the joint effect of theses dummies.

Appendix 2. Panel unit root and co-integration tests

In order to analyze the dynamics of the R&D-patent relationship within an ECM framework, one must test whether the variables have a unit root and are co-integrated. Three tests on unit roots in panel data are implemented. They are the test developed by Levin, Li, and Chu (2002); the test developed by Im, Pesaran, and Shin (2003), and a Fisher-type test (Choi, 2001), denoted LLC, IPS, and Fisher, respectively, in Table A6.

The three tests are devised under the null hypothesis that all of the variables in the panel have a unit root. LLC assumes that all individuals have the same autoregressive parameter, whereas IPS and Fisher allow for heterogeneous roots and for a heterogeneous presence of a unit root. As some of these tests require a strongly balanced panel, they were performed on a restricted sample of our initial panel dataset (this restriction was based on the availability of data that would allow us to obtain the largest possible balanced panel; the number of observations therefore fell from 3,704 to 2,516).

Table A6. Panel unit root tests

P-values	NPFCORR	TRIADIC	REGIONAL	EPO	USPTO	R&D stock
LLC	1	1	1	1	1	0.79
IPS	0.79	0.63	1	1	0.28	1
Fisher	0.87	0.81	1	1	0.37	1

Notes: We include a one-year lag structure in the regressions performed in computing the test statistics. LLC: no panel-specific mean included. IPS: panel-specific mean included; cross-sectional averages subtracted from the series. Fisher: statistic based on individual Augmented Dickey Fuller statistics with associated p-values using the inverse normal transformation; panel-specific mean included; cross-sectional averages subtracted from the series.

Most of these tests do not allow for a rejection of the null hypothesis of a unit root. Therefore, the series are non-stationary. With regard to co-integration, the four panel data tests developed by Westerlund (2007) are performed for the "basic" R&D-patent model (see Table A7). Two tests (denoted G) refer to group-mean statistics and are defined under the alternative hypothesis that there is evidence of co-integration for at least one of the cross-sectional units. The second pair (denoted P) formulates the alternative, such that a rejection of the null should be taken as a evidence of co-integration for the panel as a whole.

Table A7. Panel co-integration tests

P-values	NPFCORR	TRIADIC	REGIONAL	EPO	USPTO
Gt	0	0	0	0.01	0
Ga	0	0	0	0.06	0.04
Pt	0	0	0.04	0.76	0.04
Pa	0	0	0	0.01	0

Notes: Replication of the tests presented by Westerlund (2007) on the basic R&D-patent model. They are implemented with a constant and one lag in the error correction equation.

The null hypothesis of no co-integration is rejected for most of the five dependent variables (patent indicators), indicating that the panel is co-integrated. Thus, these results seem to confirm that a long-run equilibrium level exists between the number of patents and R&D effort.

Appendix 3. Construction of the time, country, and industry effects

The variables presented in Figures 2, 3, and 4 are based on ψ_t, ψ_j, and ψ_i in equation (6), which are the time, country, and industry effects, respectively. As the dependent variable is the first difference in the log of patent filings, the fixed effects can be interpreted as the growth rate in patenting when all of the potential explanatory variables are taken into account.

Note that the fixed effects cannot be immediately recovered from equation (6). Indeed, the fact that the error correction term is left open in equation (6) means that the estimated fixed effects also include the parameter c (recall from equation (3) that c captures the rate at which research efforts lead to patent applications). For this reason, the fixed effects presented in Figures 2, 3, and 4 have been recovered in the following way. We first estimated the residuals from equation (4) and plugged them into equation (6) in lieu of the lagged long-term relationship (the expression in parentheses in equation (6)). The fixed effects of this modified specification (time, country and industry dummies – variables ψ_t, ψ_j, and ψ_i – in equation (6)) can be interpreted as the time, country, and industry components of the unexplained change in patent counts. Figure 2 presents the cumulative effect of the time dummies on patent counts, including the average industry effect, the average country effect, and the constant. Figures 3 and 4 present the parameters ψ_j and ψ_i, respectively. They are normalized to lie between 0 and 1 for ease of readability.