The R&D-Patent relationship: An Industry Perspective

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The R&D-patent relationship: An industry perspective*

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Abstract

This paper aims at contributing to the literature on the relationship between research efforts and patent counts. It is claimed that the "propensity-to-patent" should be split into an "appropriability propensity" and a "strategic propensity". The empirical contribution is based on a unique panel dataset composed of 18 industries in 19 countries over 19 years, and relies on five alternative patent indicators. The results confirm that the distinction between the two types of propensity matter. The sharp increase in patenting observed in most patent offices seems to be due to greater internationalization of patents rather than to a burst in innovations.

JEL Classification: O30, O34, O38

Keywords: propensity to patent, strategic propensity, appropriability, research productivity.

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1. Introduction

Patent-based indicators are increasingly used to assess the rate of technological change, to gauge firms' competitive positions, to measure industrial structure, or to evaluate scientific progress and knowledge spillovers. The success of patent statistics is rooted in their wide availability, their intrinsic relatedness 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 indeed set some degree of legal and quality standards.

The quality of patents as indicators of technological change has however been criticized or challenged for several decades (see Griliches, 1990). There are noticeable differences in the use of patents across firms, industries and countries, which make patent data rather difficult to interpret. It is well known that not all inventions are patentable and that not all patentable inventions are actually patented. In addition, patented inventions differ in their quality or "inventive step." This latter shortcoming means that patents vary greatly in their technical and economic significance, with a majority of patents apparently mirroring minor technological improvements and small economic value. A growing stream of research has therefore analyzed the extent to which patents are a reliable indicator of technological change. Schmookler (1957) provides what is probably the first formal attempt to investigate what patent statistics actually indicate. Since then, the literature has mainly focused on correlations between patent counts and one or several other variables that measure either innovative input, such as R&D expenditures, or ultimate output measures, such as productivity growth or the stock market value of firms.

Studies on the R&D-patent relationship performed on cross-sectional or panel data at the firm, region or country level lead to the conclusion that there is a significant correlation between R&D inputs and patent counts. However, the estimated elasticity varies greatly with the specification of the model. While some authors report a strong impact of R&D efforts, other fail to establish a clear link between R&D and patent counts. Patents do react to firm changes in R&D expenditures, but much less than expected. Investigations at the industry level are scarce and lead to even more inconclusive results, with a weak or almost absent correlation between R&D and patents. Some industries have a high propensity to rely on the patent system but file much fewer patents than other industries with a weaker orientation towards patent protection (Levin *et al.*, 1987). This conundrum is probably what led Zvi Griliches (1990) to conclude that it would be "*misleading to interpret such [patent] numbers as indicators of either the effectiveness of patenting or the efficiency of the R&D process*." The tacit convergence amongst research scholars has been that patent data would reflect a propensity behaviour, rather than innovation performance or research productivity. This belief is reinforced by the strong increase in the number of patent filings observed worldwide over the last two decades.

This paper aims at re-visiting the failure to establish a clear empirical link between changes in patent filings and changes in R&D expenditures at the industry level. The intended contribution to the literature is both conceptual and empirical. In addition to differentiating the "research productivity" effect from the "patent propensity" effect, it is claimed that the patent propensity should be split into two main components: the "appropriability propensity" and the "strategic propensity". The appropriability propensity relates to the share of inventions that are patented by firms, as measured in classical surveys (*e.g.* Levin *et al.*, 1987; Arundel and Kabla, 1998 or Cohen *et al.*, 2000). The strategic propensity is defined as the number of patents filed to protect a given invention and has barely been measured so far. Not taking into account the two types of patent propensity might partly explain the failure to identify a strong relationship between research activities and patent applications at the industry level.

The empirical contribution of the paper is twofold. It first consists in evaluating the R&D-patent relationship with a unique panel dataset covering 18 industries in 19 countries over 19 years (1987-2005). Most studies on the determinants of patent performances are performed at the firm, regional or country levels but rarely at the industry level.[1] Yet, patent practices are known to vary widely across industries. Second, it relies on five patent-based indicators – including new ones – to test the robustness of the results: priority filings, "regional" filings and triadic filings.[2] Priority filings are first applications at national patent offices, which can be converted into regional patents later on (such as the European patent office (EPO) for Belgian applicants or the US Patent Office (USPTO) for Canadian applicants) or into triadic patent applications (patents filed simultaneously at the USPTO, the EPO and the Japanese Patent Office (JPO)). The average quality or value of patent indicators is low for priority filings and high for triadic applications, as witnessed by a larger geographical coverage and higher expenses due to legal and attorney fees, as well as translation costs.

The paper is structured as follows. The next section summarizes the results of key empirical studies on the R&D-patent relationship and introduces the two components of the propensity to patent. 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 concludes and puts forward policy implications.

The results confirm, first, that the research productivity dimension matters and explains part of the variation in the patent-to-R&D ratio. The long-term elasticity of patents with respect to R&D is of about 0.12. Second, taking into account the two components of the propensity to patent – appropriability propensity and strategic propensity – helps to refine the relationship between R&D and patents at the industry level. These two components have a positive and highly significant impact on patent counts and shed light on the strong variability in the patent-to-R&D ratio across industries.

The results also allow to better understand the current boom in patent applications. A few specific industries (computers and communication technologies) and countries (South Korea, Spain and Poland) have strongly increased their propensity to file patents, regardless of the patent indicator that is used. Generally, however, the propensity to file patents has been roughly constant for priority filings but has strongly increased for regional applications (filings at the USPTO or at the EPO). The results therefore suggest that the patent explosion observed in large regional patent offices is more the result of a globalization process than of a burst in productivity or a particularly stronger strategic propensity to file patents.

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[1] To the best of our knowledge, the study of Meliciani (2000) is the only panel-based industry level analysis. It is performed for 15 industries in 12 countries over 20 years.

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

2. A missing link at the industry level?

The estimated elasticity of patents with respect to R&D is generally found to be positive and highly significant but its amplitude varies greatly depending on the econometric specifications and the level of analysis. Table A1 in Appendix 1 presents a non-exhaustive literature review on the R&D-patent relationship. The variation is illustrated in most firm-level analyses (see *e.g.* Hausman *et al.*, 1984; Hall *et al.*, 1986; Jaffe 1986; Cincera, 1997; Duguet and Kabla, 1998; Crépon *et al.*, 1998; Blundell *et al.*, 2002 or Czarnitzki *et al.*, 2009) as well as in more "aggregate" level analyses (see for instance de Rassenfosse and van Pottelsberghe, 2009 at the country level and Bottazzi and Peri, 2003 at the regional level). The strong fluctuation of the elasticity questions the relevance of patent measures as indicators of innovative output. Three potential explanations can be put forward to explain the discrepancy. First, R&D indicators encompass much more than the very activity that consists in generating new ideas and inventions. In other words, R&D might not be a good indicator of innovative efforts. Second, R&D expenditures represent only a fraction of the total resources a firm devotes to its innovative activities. Using detailed data for the Netherlands in 1992, Brouwer and Kleinknecht (1997) have estimated that R&D expenditures represent about one quarter of total innovation expenditures. Investment in fixed assets, market research and trial production are as many expenses that are not accounted for by official statistics. Third, patent series are by nature subject to a substantial bias, with most patents generating low or no value and a few patents being associated with a high economic of financial value. More generally, the estimates could be impacted by the patent count that is used. Studies rarely test the sensitivity of their results to the patent count methodology or the data source used. In this respect, there is a clear need for a comparative study of the various patent indicators.

Industry level analyses lead to even less conclusive insights into the R&D-patent relationship (see Meliciani, 2000). Cross-industry differences in the patent-to-R&D ratio exhibit great variations and do not necessarily correlate with their perception of the effectiveness of patents as a protection mechanism. For instance, some R&D-intensive industries that systematically rely on the patent system such as the pharmaceutical industry show low patent-to-R&D ratios, suggesting that patent metrics do not correlate well with innovative efforts across industries.

Scholars have long argued that patent counts reflect more the propensity to patent than innovative performance or research productivity. For instance, Scherer (1983, p. 116) explicitly assumes a constant productivity of research, for the sake of simplicity. While admitting the possibility of "differential creativity of an organization's R&D scientists and engineers", the author does not consider it important and chooses to concentrate on other "more systematic" factors. These more "systematic" factors which drive the patenting performance of firms are of two main types: alternative protection mechanisms and strategic behaviour.

First, companies have varying capacity for appropriating innovation rents. They rely on many alternative mechanisms of appropriation, such as secrecy, lead time, complementary sales and services, complementary manufacturing facilities, barriers to entry and tacit knowledge. These mechanisms may coexist with patent protection and are often paired with it. According to the Carnegie Mellon Survey by Cohen *et al.* (2000) or the survey by Arundel and Kabla (1998), patents appear to be generally the last appropriability mechanism that is used, though its importance for some industries is noticeable, as reported in Table 1. This is particularly true for pharmaceuticals, machinery, and office and computing equipment. Secrecy and lead time are ranked overall as the two most effective appropriability mechanisms being top-ranked in 17 and 13 industries, respectively. Based on survey data of R&D executives in Switzerland, Harabi (1995) reports that the ability of competitors to “invent around” patents and the perception that patent documents disclose too much information are the most important factors that reduce the willingness to file patents.

The second reason that undermines the quality of patents as indicators of technological advance is to be found in strategic patenting, a topic of investigation for the past 20 years (*e.g.*, Teece, 1998; Rivette and Kline, 2000; Guellec *et al.*, 2007). Applying for a patent is indeed not always driven by the desire to protect innovation rents: Patents can be used as a tool for technological negotiations with competitors or with potential collaborators, to exclude rivals from a particular technological area, for communication purposes, to increase revenues through license agreements, to ensure freedom to operate and to attract capital. These strategic considerations all influence the observed patenting performance of firms. Patents are therefore not only an indicator of innovation output and technological success but also an indicator of strategic behaviour (see Blind *et al.,* 2006; Cohen *et al.,* 2000; de Rassenfosse and Guellec, 2009 or Hall and Ziedonis, 2001 for detailed investigations in this field).

Table 1. Share of product innovations that are patented (in percent)

	Arundel and Kabla (1998)	Cohen *et al.* (2000)
Mining	28	-
Food, beverages and tobacco	26	53
Textiles, clothing	8	43
Petroleum refining	23	73
Chemicals	57	77
Pharmaceuticals	79	74
Rubber and plastic products	34	65
Glass, clay, ceramics	29	50
Basic metals	15	54
Fabricated metal products	39	77
Machinery	52	74
Office and computing equipment	57	80
Electrical equipment	44	62
Communication equipment	47	59
Precision instruments	56	70
Automobiles	30	89
Other transport equipment	31	-
Power utilities	29	41
Transport and telecom services	20	-

Notes: The industry classification corresponds to that presented in Arundel and Kabla (1998).
The shares are rounded to the nearest integer.

In a nutshell, beside the innovation output that requires protection, the decision to file a patent is affected by alternative mechanisms of appropriation and by the strategic role that patents can play for a firm. These elements are typically industry-specific. It is striking that despite the many sources of variation and randomness in patent data, there has been a continuous increase in the use of patent-based indicators, not least for economic and strategic analyses. The objective of this paper is to reconcile the *a priori* antagonism between the intensifying use of patent data and the pessimistic appraisal of these indicators in the economic literature. This reconciliation is done by identifying key milestones when analyzing the R&D-patent relationship at the industry level and by performing the empirical analysis with various patent indicators.

A first distinction can be made with respect to two important factors: research productivity and patent propensity. This distinction is investigated at the macroeconomic level by de Rassenfosse and van Pottelsberghe (2009) who find that patent indicators reflect both effects. The authors exploit the cross-country variation in patent indicators for the year 2003. They relate the number of patents to aggregate R&D expenditure and to proxies for research productivity (*e.g.* the share of basic research in total R&D) and propensity to patent (*e.g.* the cost of filing a patent or the strength of the patent system). Unlike the present study, however, the authors have limited insights into cross-industry differences in the propensity to patent and do not investigate the time dimension, including the dynamic adjustment of patent outcomes to changes in research efforts.

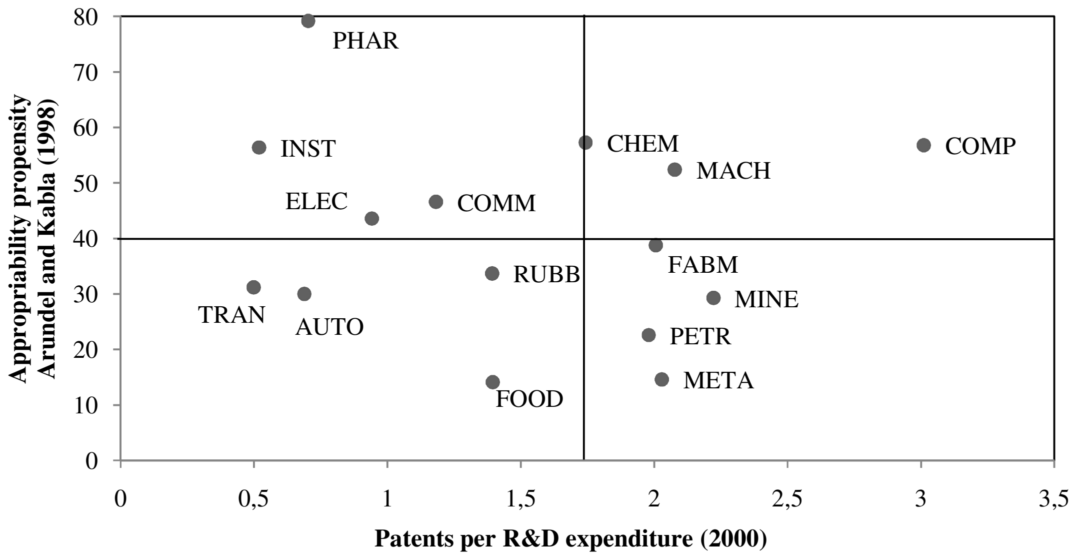
The literature on the R&D-patent relationship has taken the implicit practice to define "patent propensity" in a (too) broad way as the number of patents per R&D. The propensity could however be defined as the number of patents per invention and be split into two components: the "appropriability propensity" and the "strategic propensity", as illustrated in Figure 1. The former captures the decision to protect an invention and is measured with the share of inventions that are patented, as reported in surveys such as Cohen *et al.* (2000) or Arundel and Kabla (1998). The latter captures the patent-filing behaviour at a second stage. Once the decision is made to protect an invention, the applicant chooses the number of patents that are to be filed to protect it. Early evidence by Reitzig (2004) supports the claim put forward in this paper. Using survey data for 614 patents filed at the EPO, the author finds that on average inventions are protected by a coherent group of around five patents. These two dimensions surely affect the observed R&D-patent relationship. The failure to distinguish the appropriability propensity from the strategic propensity is probably what made Griliches (1990) claim that "*the patent to R&D ratios appear to be dominated by what may be largely irrelevant fluctuations in the R&D numbers*." This paper argues – and provides empirical evidence of the claim – that taking into account these two dimensions provides a better understanding of the R&D-patent relationship.

Figure 1. The R&D-patent relationship

Figure 2 illustrates the issue at stake. It depicts the appropriability propensity on the vertical axis against the ratio of patents to R&D expenditures on the horizontal axis. For instance, the instrument and the computer industries have a high appropriability propensity but the latter has a much higher patent-to-R&D ratio than the former, probably due to a higher strategic propensity (patent thickets are known to be prevalent in this particular industry). Note that differences along the horizontal axis are probably not solely due to heterogeneous strategic propensities. The pharmaceutical industry has a very high appropriability propensity but a very low patent-to-R&D ratio due to the large amount of R&D efforts devoted to a single invention. Similarly, the relatively low share of patented inventions in food and basic metals does not prevent these industries from having a relatively high number of patents per R&D. This should be borne in mind when interpreting statistics such as patents over R&D

expenditures. The quantitative approach adopted in the next section aims at taking into account, and measuring, these three components (productivity, appropriability propensity and strategic propensity) of the R&D-patent relationship.

Figure 2. Appropriability propensity and the R&D-to-patent ratio by industry



Source: Arundel and Kabla (1998) and own calculations

Note: The horizontal axis corresponds to the ratio of priority filings to R&D expenditures (in million of USD PPP at constant prices).

3. Empirical implementation

The aim of the empirical analysis is to investigate the link between R&D and patents at the industry level with several alternative patent indicators and taking into account the factors that affect the propensity to patent and those that affect the productivity of research efforts. In an ideal set-up, one would be able to observe both the "raw" technology output (*i.e.* the number of inventions) and the number of patents. Yet, since the only observable measure of inventive output is the count of patents, one should be cautious when interpretating 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 ($t = 1, \ldots, 19$), industry (i=$1,\ldots,18$) and country ($j=1,\ldots, 19$). Each "individual" is thus an industry–country pair.[3] Since 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 (forgetting momentarily the time dimension):

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

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

where Ω and Φ are diagonal matrices of size N capturing the productivity and the propensity effects for each individual, respectively. In this framework, Φ captures both the appropriability propensity and the strategic propensity. The parameter γ is a scalar measuring the average return to R&D across individuals [4]. Φ can be expressed as a function of the two propensity components (the appropriability propensity and the strategic propensity) 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 α and β the column vectors of parameters, equation (1) can be written as:

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

where lower-case roman letters denote the log of the variables. Expanding the patent production function gives:

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

where c equals $c_1 + c_2$ and 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 the average propensity to file patents). It is well documented in the literature (see the introduction and Section 2) that the propensity to patent has most probably increased since the eighties, due to an unobservable greater reliance on the patent system for various "strategic" reasons, *i.e.*, c_2 might have increased over time, even when accounting for the observable characteristics Z. In a similar vein, the productivity of research has also probably improved over the years (Kortum and Lerner, 1999). Therefore, the extent to which the scale variable c would capture an average growth rate of the productivity of research or of the two propensity effects is unclear. It actually depends on the proxies used to measure research productivity and patent propensity. As the variables used in the empirical analysis tend to better capture cross-industry and cross-country variations in the productivity of research, there are more reasons to suspect that unobserved changes are due to variation in the propensity to patent rather than in the productivity of research. It is therefore likely that the dummies (country, industry or year effect) would be more reflective of a change in propensity than a change in productivity. The patent production function for a given industry-country pair in 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 in first-difference to avoid potential spurious-regression problems. Letting "Δ" denote the first-difference operator, equation (4) can be transformed as follows:

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

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

Assuming that c_1 is roughly constant,

$$\Delta c_{ijt} = c_{ijt} - c_{ijt-1} = (c_{1,ijt} + c_{2,ijt}) - (c_{1,ijt-1} + c_{2,ijt-1}) \approx \Delta c_{2,ijt}, \tag{6}$$

such that

$$\Delta p_{ijt} = \Delta c_{2,ijt} + \gamma \Delta r_{ijt} + \beta \Delta z_{ijt} + \alpha \Delta x_{ijt} + \upsilon_{ijt}, \tag{7}$$

with $\upsilon_{ijt} = \Delta\varepsilon_{ijt}$. Since the variables are expressed in logs, equation (7) is an approximation of the growth rate of patenting. The term $\Delta c_{2,ijt}$ is the growth rate of the propensity to patent that is not accounted for by the explanatory variables. Equation (7) implies that a change in any of the explanatory variable has a contemporaneous impact on the number of patents applied for. In other words, the parameters of the first-differenced variables capture the short term elasticities.

However, past R&D expenditures might also influence current patenting activity because research projects usually require some time before leading to a patentable invention. In order to account for a gradual adjustment, the patent production function is estimated by means of an error correction model (ECM)[5] with a one-year lag structure. The choice of a one-year lag is motivated by de Rassenfosse and Guellec (2009) and Hall *et al.* (1986)[6]. Using firm-level survey data, de Rassenfosse and Guellec (2009) notice that the lag between initial R&D expenditures and patent applications is of the order of one year, even though it can reach as much as five years. Hall *et al.* (1986) estimate several panel data models at the microeconomic level and obtain a strong contemporaneous relationship between R&D expenditures and patenting, and 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.

ECMs allow estimating both the short-run and the long-run impacts that exist between the endogenous and the exogenous variables. It consists in estimating the model in first difference together with previous year's deviation from equilibrium (in brackets), leading to the following equation to be estimated:

$$\Delta p_{ijt} = \psi_i + \psi_j + \psi_t + \gamma_s \Delta r_{ijt} + \beta_s \Delta z_{ijt} + \alpha_s \Delta x_{ijt} - (\lambda p_{ijt-1} - c - \gamma_l r_{ijt-1} - \beta_l z_{ijt-1} - \alpha_l x_{ijt-1}) + v_{ijt} \tag{8}$$

Finally, remember that the individual is defined as a country-industry pair. The term $\Delta c_{2,ijt}$ of Equation (7) can be decomposed into a fixed industry effect (ψ_i), a fixed country effect (ψ_j) and a common time-effect (ψ_t).

The term between parentheses 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 (*i.e.* those preceded by the operator Δ) capture the short-term impact on the number of patents and 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

[5] The tests on unit roots and cointegration for our panel data (see Appendix 2) suggest that the series are non-stationary and cointegrated. It confirms the interest of an ECM framework for the analysis of the R&D-patent relationship at the industry level.

[6] Kondo (1999) analyses the dynamic mechanism of the R&D-patent relationship of Japanese industry and shows also that the R&D effort create patent applications with a time-lag of about a year and a half.

the adjustment process). The long-run elasticities are calculated by dividing each parameter associated with the lagged variables by the adjustment parameter λ. For instance, the long-run elasticity of the productivity variable is equal to $-\alpha_l \cdot \lambda^{-1}$ (for a discussion, see Alogoskoufis and Smith, 1991).

3.2 The dependent variable: patent indicators

There exist many ways to count patents, each having its own strengths and weaknesses (see *e.g.* Dernis *et al.,* 2001 and OECD, 2009 for a discussion). It is therefore particularly important to carefully select the patent indicators that will be used to monitor countries' innovation performance so as to reduce the potential biases as much as possible. For this reason, five alternative indicators are used in the 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 (the so-called 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 supposed to be of a much higher economic value.

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. Patents, however, are not characterised by the ISIC scheme, but rather by the codes of the International Patent Classification (IPC), representing 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). The authors have estimated the empirical concordance table by investigating the patenting activity by 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.[7]

The first indicator is the corrected count of national priority filings (NPFCORR) recently introduced by de Rassenfosse *et al.* (2010). It captures all the patents filed by the inventors based in a country, regardless of the patent office of application. The count for, say, Austria is thus equal to the number of priority filings invented by inventors based in Austria and filed at the Austrian patent office plus the priority filings invented in Austria but directly filed at other patent offices such as the EPO, the USPTO or the German patent office. This methodology assures the best match between R&D expenditures and patent applications at the country level. The inclusion of these priority filings abroad also allows reducing the bias against small countries such as Belgium and the Netherlands which file a high share of their patents abroad as compared with larger countries such as France or Germany. This corrected count of priority filings is a broad measure of patenting, encompassing both low-value and high-value patents. It is biased in favour of Japan and South Korea, with the share of these countries in the total of national priority filings being much higher than their share in R&D expenditures. This is due to the large differences in patent systems, particularly in South Korea and Japan, where patents are much smaller in scope but more numerous: these patents have on average three times less claims than US or European patents. For this reason, the

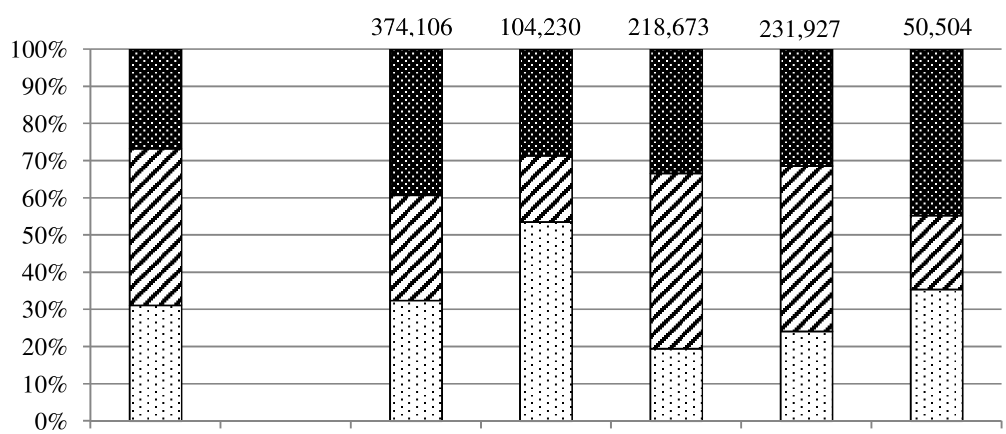
[7] Some patents had no IPC codes, and some IPC codes were not in the concordance table. All these "unassigned" patents were allocated to the industries according to the observed share of successfully allocated patents.

count for Japanese and Korean priority filings has been divided by three (for a discussion, see Kotabe, 1992 and Archontopoulos *et al.*, 2007).

The second indicator is the count of patent applications filed at the EPO. It is composed of the patents that were filed directly at the EPO or that were later extended to the EPO as second filings. As the patenting procedure at the EPO is expensive, EPO patents are supposedly of a higher value. This indicator is nevertheless biased for two main reasons. The first is related to the home bias, which is well illustrated in Figure 3, whereby companies in Europe tend to file a higher proportion of their patents at the EPO as compared with companies from non-European countries. Second, the reliance on the EPO has increased over time, for all countries and especially European ones. de Rassenfosse and van Pottelsberghe (2007) show that a systematic bias in statistics based on European patents must be acknowledged: the share of priority filings transferred to the EPO is increasing with the age of membership to the European Patent Convention. This calls for a cautious interpretation of the evolution of the number of EPO patents over time.

The third indicator is similar to the second, except that the patent office of reference is the USPTO and that long-term statistics are available for granted patents. Given that a large number of countries in the sample are European countries, this indicator probably reflects the value of patents better (a European applicant will file more easily at the EPO than at the USPTO, and will seek for a US patent only for the most valuable inventions).[8] However, this indicator is subject to an important, and logical, home bias for North American applicants as illustrated in Figure 3.

Figure 3. Research effort and patenting activity, 2004



Source: Own calculations.

The fourth indicator (REGIONAL) is a mix between EPO and USPTO patents. Since European applicants have a higher tendency to file at the EPO and other countries preferably file at the USPTO, the indicator is composed of EPO patents for European countries and

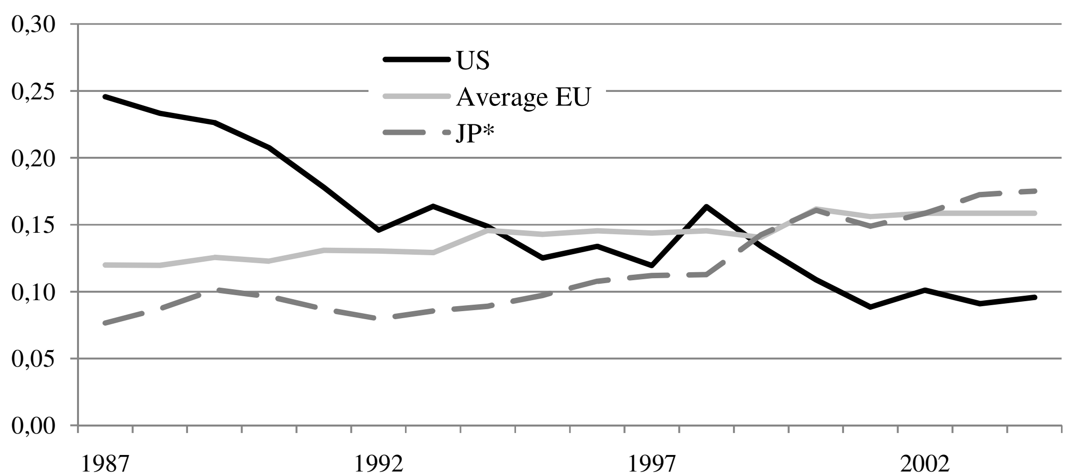
[8] To mitigate the effect of the grant lag on US patent statistics, which was especially strong in 2004 and 2005, the data are adjusted for each country-industry pair using the ratio of EPO patents to US patents for the year 2003.

USPTO patents for other countries. The approach mitigates the home biases characterising the EPO and the USPTO indicators, with a geographical distribution that is closer to the distribution of research efforts.

The count of triadic patent families is the fifth indicator (TRIADIC). It was developed a decade ago by the OECD to select patents of a high quality standard that were comparable across countries. According to the OECD definition, the triadic patent family is defined as "*a set of patent applications filed simultaneously at the EPO, the JPO, and granted by the USPTO*", sharing one or more priority applications (OECD 2009: p. 71). The 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 incurred with patent applications in the three patent offices. On average, only between 10 and 15 percent of priority filings ultimately become triadic patents. The 19 countries included in the sample have a total of 374,106 priority filings in 2004 for 50,504 triadic patent applications. The absolute count of patents and the relative shares are presented in Tables A3 and A4 of Appendix 1 for countries and industries, respectively.

Figure 4 represents the share of priority filings that eventually became triadic patents. de Rassenfosse and van Pottelsberghe (2009) have shown that triadic patents are more suited than priority filings to capture the productivity of research efforts. Yet, an increase in the share of triadic patents over time might also be associated with an increase in the internationalisation of economic activity witnessing a more competitive economy. The figure shows that the share of triadic patents has been slightly increasing in Europe and Japan and literally falling in the US. The increase in Europe and Japan could be due to a higher tendency of applicants to seek protection in foreign markets. For the US it is likely that the drop in the share of triadic patents is due to a strong increase in the number of priority filings that did not lead to many triadic patent applications. According to van Pottelsberghe (2009) this is due to the very low cost of patenting in the US and a weak rigour of the examination process. A cheap patent system with a soft examination practice would logically lead to a high propensity to file low value patents that do not reach the minimum value threshold to be turned into triadic applications.

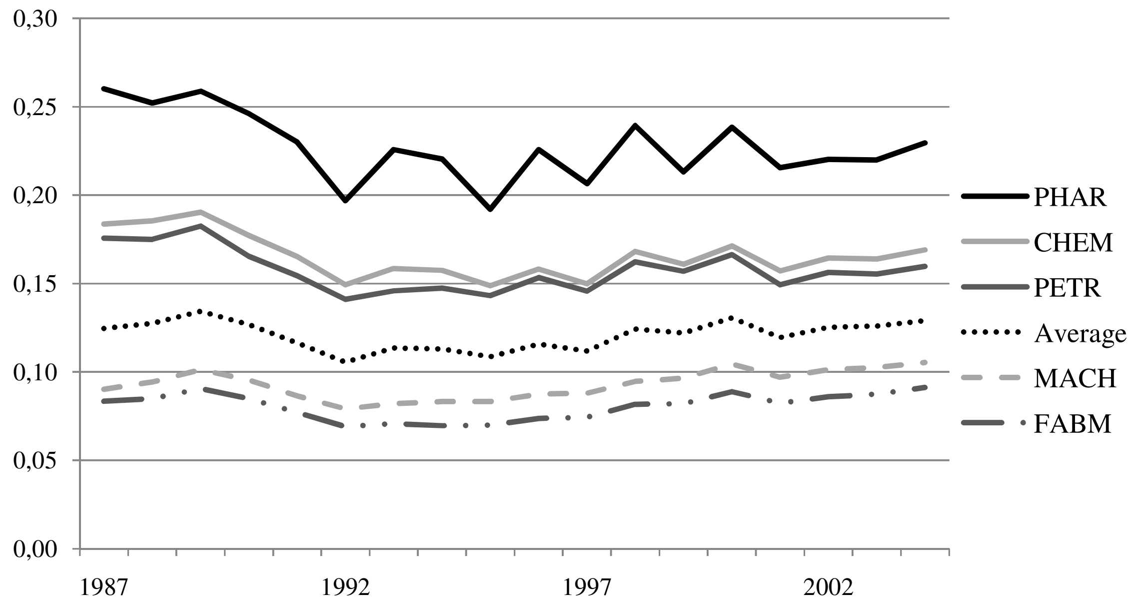
Figure 4. Share of triadic patents in total priority filings, in Europe, Japan and the USA



Source: Own calculations
Note: CH and NO are included in Average EU.

Figure 5 depicts the evolution over time of the share of triadic patents for a selected number of industries. On average, 10 to 15 percent of priority filings became triadic, but some industries, in particular the pharmaceutical industry have a much higher share of triadic patents. This figure should be contrasted with the low ranking achieved by the pharmaceutical industry in Figure 2. This industry typically produces a low number of patents per unit of R&D, but these patents are of a relatively high value.

Figure 5. Share of triadic patents in total priority filings, selected manufacturing industries



Source: Own calculations, see Table A2 for the industry definitions.

3.3 Explanatory variables

The most important explanatory variable is R&D expenditures by industry (R&D) as a measure of the industry's research efforts. It is taken from the OECD's ANBERD database and is expressed in constant 2000 US dollars (USD) at purchasing power parity (PPP). The estimated patent elasticity with respect to R&D provides an incomplete evaluation of the research productivity. A more complete picture would be easy to draw if inventions (not patents) could be measured with accuracy and if the two types of propensity to patent were properly measured across countries and over time. Since there are no such indicators, an indirect approach such as the one developed by de Rassenfosse and van Pottelsberghe (2009) is needed. It consists in finding variables that arguably reflect (or induce) differences in the productivity of research activities and variables that arguably affect the propensity to patent.

Finding potential explanatory variables affecting the propensity and the productivity components for a large group of countries, varying over industries and available over a long period is a challenging task. Three candidates that could affect the productivity of research and three others potentially affecting the propensity to patent were identified. Some vary over time and across countries and industries whereas some others vary only across countries or industries, as indicated in Table 2.

Table 2. Overview of the explanatory variables

	Component		Variation			Number of observations
	Propensity (z)	*Productivity (x)*	*Country*	*Industry*	*Year*	
R&D			x	x	x	4937
APPROPRIABILITY	x			x		4131
COMPLEXITY	x			x		4937
IP INDEX	x		x		x	4937
INTL COMP		x	x	x	x	4451
SHARE BASIC		x	x		x	1811
SHARE HIGHER EDU		x	x		x	4353

Source: OECD STAN R&D Expenditure in Industry (ISIC Rev. 3) ANBERD ed2009 for R&D; Arundel and Kabla (1998) for APPROPRIABILITY; von Graevenitz et al. (2008) 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; OECD STAN Bilateral Trade Database for INTL COMP; and OECD Main Science & Technology Indicators for SHARE BASIC and SHARE HIGHER EDU

The three variables that are supposed to affect – or to correlate with – research productivity are defined and measured as follows. The variable "SHARE BASIC" is the basic-research expenditure as a percentage of gross domestic expenditure on R&D (OECD Main Science & Technology Indicators (MSTI)). The variable is expected to lead to a greater productivity of research efforts as basic research typically pushes forward the knowledge frontier and generates new opportunities for further development. The second productivity variable is "SHARE HIGHER EDU." It is defined as the percentage of gross domestic expenditure on R&D performed by the higher education sector (OECD MSTI). The expected impact on the number of patents is mixed. On the one hand, the higher education sector develops and uses frontier knowledge that 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 third productivity variable is "INTL COMP" and captures an industry's exposure to international trade. It is defined for each country-industry pair as the ratio of net exports to the sum of imports and exports (OECD STAN Bilateral Database). The higher the ratio, the more the industry exports in comparison to its imports, hence the more it is internationally competitive. A positive impact is expected as internationally competitive industries must be innovative in terms of new product performance or reduced production costs. In analysing the determinants of patenting across a set of OECD countries, Furman *et al.* (2002, p. 899) find that "an extremely important role is played by factors associated with differences in R&D productivity [such as] openness to international trade."

Three proxies are used to measure the propensity effects. The first variable, "APPROPRIABILITY", captures the appropriability propensity and is based on a survey of the share of innovations that were patented in the French manufacturing industry (Arundel and Kabla, 1998). This observation allows reducing 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 of the ANBERD database. As for the strategic propensity, the variable "IP INDEX" is a measure of the strength of the intellectual property (IP) system at the country level developed by Ginarte and Park (1997) and updated by Park (2008). We expect countries with a stronger IP regime to have a higher strategic propensity to patent as a strong protection increases the value of patent rights and signal a more advanced patent system.[9] This is an imperfect proxy however, as it is only published every five years and is rather stable over time.[10] The second proxy for the strategic propensity is the measure of 'complexity' developed by von Graevenitz et al. (2009). They construct a novel measure of patent thickets by technology area based on 'triples' of firms that mutually block some of each others' patents (variable COMPLEXITY). They identify the most complex technology areas as being those with the highest density of 'triples'. This information derives directly from data on European patent citations. In our industry perspective, an own industry matching of the median number of 'triples' was considered as a factor explaining the variation in strategic propensity across industries.

It must be emphasized that the variables that supposedly correlate with the productivity of research are more diverse and comprehensive than the propensity variables: the exposure-to-trade variable varies across countries, industries and over time and the other two variables (SHARE BASIC and SHARE HIGHED EDU) vary over time and across countries. By contrast, the proxies for the appropriability propensity and for the complexity vary only across industries, while the IP INDEX varies only slightly across countries and over time. It is therefore fair to assume that the fixed effects in the regression mainly capture changes in the propensity to patent across the various dimensions of the panel (industry, country and time) as assumed in equation (6).

4. Empirical results

The empirical results are presented and interpreted in three main stages. First, the basic R&D-patent model is estimated with the five patent indicators. Then the productivity and the propensity variables are added simultaneously to the model. The third stage consists in analyzing the various sets of dummies (industry, country and time), as they witness the remaining "dynamic" propensity to patent.

4.1. The basic R&D-patent model

The estimated parameters of the error correction model described in Equation (8) are presented in Table 3 for the five patent indicators. The only explanatory variable taken into account is R&D expenditure.

[9] van Pottelsberghe (2010) 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 actually likely to increase the strategic propensity.

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

Table 3. Results of the error-correction model of the R&D-patent relationship

Δ log(#patents)	NPFCORR (1)	TRIADIC (2)	EPO (3)	USPTO (4)	REGIONAL (5)
Δ log(R&D)	0.009	0.013	0.009	-0.013	0.014
	(0.007)	(0.015)	(0.009)	(0.010)	(0.009)
log(#patents) (t-1)	-0.119***	-0.290***	-0.155***	-0.145***	-0.149***
	(0.007)	(0.010)	(0.008)	(0.008)	(0.008)
log(R&D) (t-1)	0.014***	0.032***	0.018***	0.017***	0.019***
	(0.002)	(0.005)	(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	4943	4943	4943	4943	4943
Adjusted R-squared	0.197	0.187	0.156	0.171	0.129
Long-run impact of R&D	0.118***	0.110***	0.116***	0.123***	0.128***

Notes: Standard errors in parentheses; ***, **, * denote significance at the 1, 5 and 10-percent levels, respectively. The rows "country dummies", "industry dummies" and "time dummies" report the significance level of the joint effect of theses dummies. The long-run impact of R&D is computed by dividing the coefficient of log(R&D) (t-1) by the coefficient of log(#patents) (t-1).

The short-term elasticity of patents with respect to R&D is not significantly different from zero (see the parameter associated with Δlog(R&D)). This result suggests that changes in patent filings are a poor indicator of contemporaneous changes in R&D expenditures. The long-term elasticity of R&D is highly significant and fluctuates around 0.12 as indicated in the last row of Table 3. In other words, a 10-percent increase in R&D outlays leads to a 1.2-percent increase in patent applications, on average. Two remarks must to be made regarding these estimated long-term elasticities. First, the various point estimates are strikingly low but compatible with estimates performed with firm-level panel data sets. Second, the elasticity is very stable across patent counts. In other words, studies that use different patent indicators have some degree of comparability. This stability is all the more remarkable given the strong variations in the adjustment parameter.

Depending on the patent indicator that is used, R&D expenditures and the fixed effects explain between 13 and 20 percent of the growth in patent applications. The best fits are achieved with priority filings and triadic patents, *i.e.* the patent indicators that are at the opposite ends on the value scale. This better performance is probably due to the fact that these two indicators are the least subject to home bias. The explanatory power is fairly high given 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 analysed at the end of this section. Note that the tests for autocorrelation of residuals reject the presence of correlated errors.

4.2. Productivity

The low estimated elasticity of patents with respect to R&D raises the question of whether other factors may help to explain industry or country variations in patent applications. This issue is investigated in Table 4 where the productivity and the propensity components are jointly included in the model. The estimations are presented only with NPFCORR, TRIADIC and REGIONAL patent indicators as dependent variables for the sake of readability. Regressions based on EPO and USPTO lead to very similar results.

Table 4. Results of the full error-correction model

Δ log(#patents)	NPFCORR (1)	TRIADIC (2)	REGIONAL (3)
APPROPRIABILITY	0.004***	0.012***	0.005***
	(0.000)	(0.001)	(0.000)
IP INDEX	0.031***	0.053**	0.073***
	(0.012)	(0.023)	(0.015)
COMPLEXITY	0.003***	0.005***	0.003***
	(0.000)	(0.000)	(0.000)
Δ log(R&D)	-0.003	-0.010	-0.008
	(0.008)	(0.016)	(0.010)
Δ INTL COMP	-0.002	0.098***	0.052***
	(0.016)	(0.030)	(0.019)
Δ SHARE HIGHER EDU	-0.010***	-0.002	-0.008***
	(0.002)	(0.004)	(0.002)
log(#patents) (t-1)	-0.142***	-0.279***	-0.137***
	(0.008)	(0.012)	(0.009)
log(R&D) (t-1)	0.014***	0.013**	0.007*
	(0.003)	(0.006)	(0.004)
INTL COMP (t-1)	0.028***	0.100***	0.056***
	(0.009)	(0.017)	(0.011)
SHARE HIGHER EDU (t-1)	0.0001	-0.002	0.005***
	(0.001)	(0.002)	(0.001)
Countries dummies	Yes ***	Yes ***	Yes ***
Industry dummies	Yes ***	Yes ***	Yes ***
Time dummies	Yes ***	Yes ***	Yes ***
Number of observations	3696	3696	3696
Adjusted R-Squared	0.236	0.190	0.140
Long-run impact of R&D	0.099***	0.047**	0.051*
Long-run impact of INTL COMP	0.197***	0.358***	0.409***
Long-run impact of SHE	0.001	0.007	0.036***

Notes: Standard errors in parentheses; ***, **, * denote significance at the 1, 5 and 10-percent levels, respectively. Each of the rows "country dummies", "industry dummies" and "time dummies" report the significance level of the joint effect of the respective dummies.

The three indicators that are likely to be correlated with research productivity are the share of higher education in total R&D expenditure, the share of basic research in total R&D expenditure and an indicator of international competitiveness. The first two indicators vary across countries and over time while the third fluctuates in the three dimensions. The impact of the share of total R&D performed by the higher education sector (SHARE HIGHER EDU) has a positive and significant impact on the regional patent indicator only[11], suggesting that

[11] A positive effect was also expected with triadic filings. 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.

university-performed R&D leads to more valuable patents in the long-run. The negative short-term impact of this variable is probably due to a transitional effect caused by the diversion of resources towards less patent-minded institutions. It can also be explained by longer delays in the R&D process at universities as compared with the private sector.

The share of basic research, an indicator of the relative efforts directed towards potential breakthrough inventions, is tested separately. It is not included in the main specification due to a much smaller sample. 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 a long-term premium of about 11 percent. In other words, the higher the share of basic research in total R&D expenditures, the higher the number of patent applications induced by an increase in the research productivity. It confirms that allocating more resources to basic research is a long-term policy aimed at securing the seeds of future innovations.

The exposure to international trade (INTL COMP) has a positive and significant impact on the number of patent filings, both in the short run and 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 twice as high with international patents as with priority filings, which indicates as expected a strong correlation between international competitiveness and international patenting activity. Interestingly, the long-term elasticity of patents with respect to R&D substantially drops when productivity variables are added to the model. The drop is most stringent for high value patents, underlying the strong importance of the productivity effects for these patents.

4.3. Propensity

The distinction between appropriability propensity and strategic propensity put forward in the present paper is not straightforward to implement empirically. The three proxies that are used to gauge these effects are imperfect measures because they only vary across countries or across industries and are quite stable over time. Still, the share of inventions patented (APPROPRIABILITY) is highly significant, which provides evidence of the key role played by the appropriability propensity in the R&D-patent relationship.

The variables that aims at capturing some facets of the strategic propensity are the measure of complexity (COMPLEXITY) and the strength of the patent system (IP-INDEX from Ginarte and Park, 1997 and Park, 2008). Both variables turn out to be significant determinants of the number of patents. On the one hand, complex industries (as measured by the number of blocking patents) are characterized by more patents applications per unit of R&D effort compared to more discrete technologies. On the other hand, countries with a higher IP-INDEX are also likely to have more patent filings per unit of R&D effort. For instance, the US has a very high 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 supporting patent holders. In other words, the more applicant-friendly the patent system the more patents are filed.

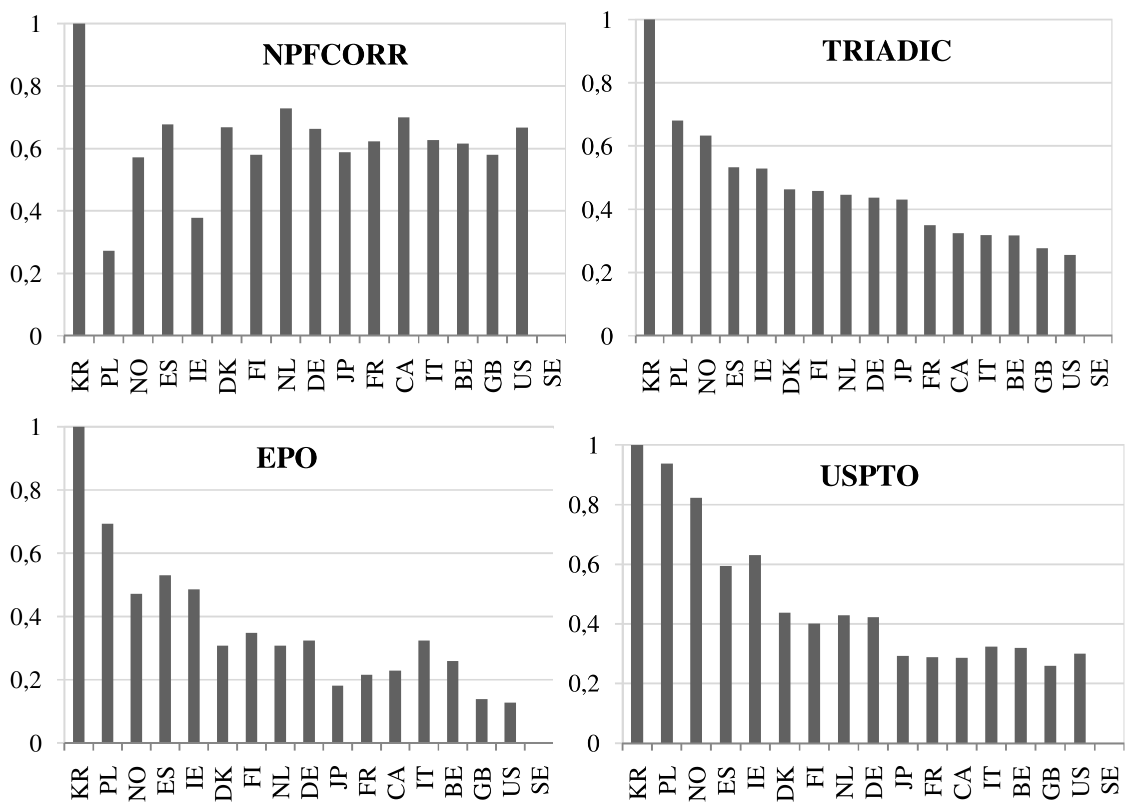
These propensity variables are only two factors influencing the strategic propensity to patent. Despite their significant impact, which validates one of the intuitions that motivated this paper, one can hardly disagree with the fact that the “strategic propensity” is imperfectly measured. To the best of our knowledge, no other indicator with cross-industry variations is available.

4.4. Remaining "dynamic" propensity

The country, industry and time effects from the full model can be used to assess the average evolution of the propensity to patent along the three dimensions (see Appendix 3 for methodological details). Since the model explains the growth rate of patent filings, the dummies capture the increase in the propensity to patent – or the "dynamic" propensity – net of the impact of all other observable characteristics. The fixed effects probably capture unobserved changes in productivity and in the two measures of propensity. But since the R&D productivity component is arguably better measured than the two propensity components, it is fair to assume that the fixed effects are more reflective of the propensity than the productivity component.

Figure 6 shows the normalized parameter associated with the country dummies. The rankings for the international indicators (TRIADIC, EPO and USPTO) are roughly similar and clearly underline a strong catching-up effect for South Korea, Poland, Norway and Spain. Countries such as France, Canada, Great Britain 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.

Figure 6. Dynamic propensity to patent across countries

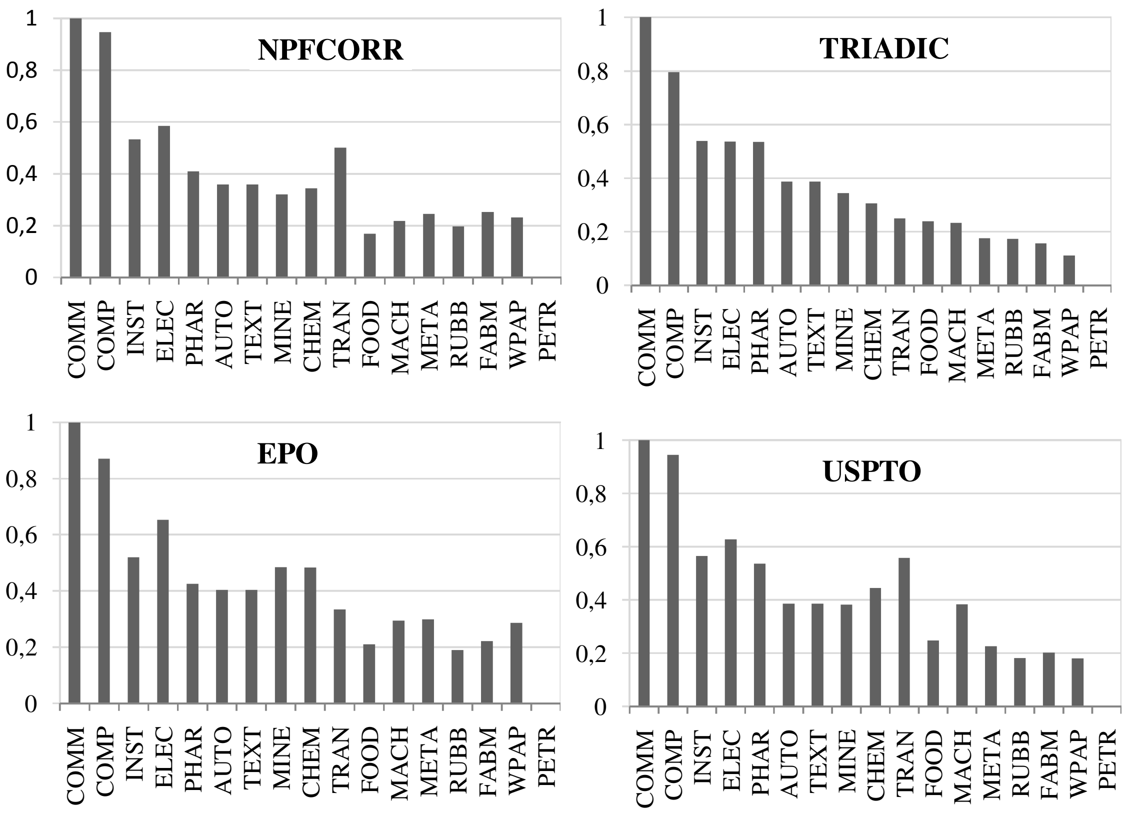


Source: Own calculations

Notes: The values are coefficients of country dummies taken from the full model and are normalized from 0 to 1; they are interpreted as normalized dynamic propensity to patent. See Appendix 3 for more details.

The change in the propensity to patent also varies to a significant extent across manufacturing industries as illustrated in Figure 7. The industries related to communication, computers and instruments are associated with the strongest increase in the propensity to patent whereas fabricated metals or rubber and plastics products had the lowest increase. There is a clear ICT (information and communication technologies) effect at play. The industries in this area already 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 catching-up effect from newcomers, the industry dummies seem to reinforce the trends towards a higher propensity to patent. As the industry-specific appropriability propensity is controlled for, this effect is most probably due to a sharp increase in the strategic propensity to patent in the two industries.

Figure 7. Dynamic propensity to patent across industries

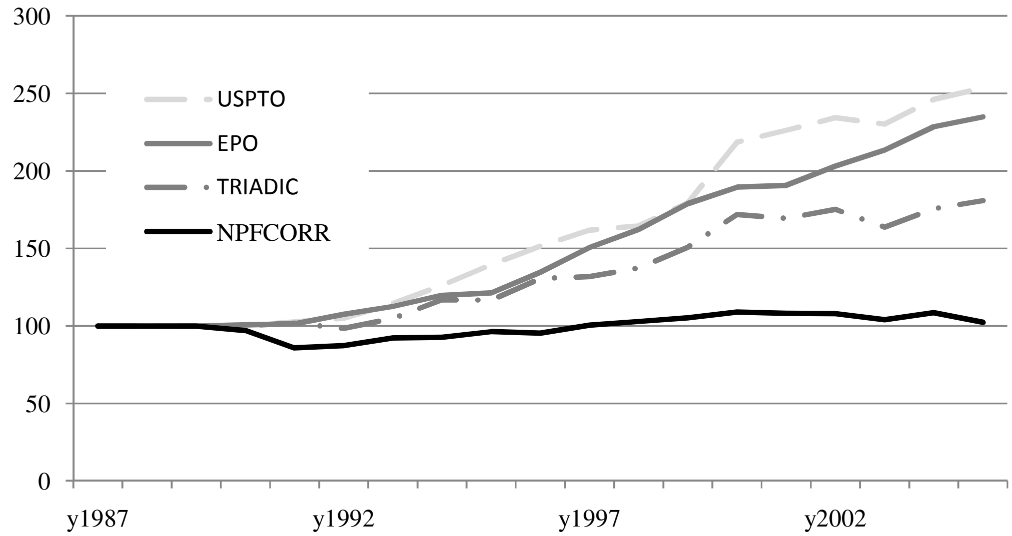


Source: Own calculations

Notes: The values are coefficients of industries dummies taken from the full model and are normalized from 0 to 1; they are interpreted as normalized dynamic propensity to patent. See Appendix 3 for more details.

Finally, Figure 8 depicts the evolution of the propensity to patent over time for the main patent indicators. 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. Taken together, these trends lead to the conclusion that there has been no particular "burst" in the underlying inventiveness (beyond the increase in R&D efforts and beyond the improvement in research productivity measured in the empirical analysis) and that the "patent warming" observed at major patent offices is mostly due to a globalization effect: companies do not file particularly more patents, but have a higher willingness to extend them abroad. The USPTO (and to a lesser extent the EPO) is particularly intensely targeted in this respect.

Figure 8. Evolution of the propensity to patent over time



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

5. Concluding remarks and policy implications

The literature on the R&D-patent relationship reports a significant correlation between R&D efforts and patents. However, the estimated elasticities vary greatly, especially when estimated at the industry level. This weakness has not prevented patent statistics to be used for many purposes, including economic research on technological progress and knowledge diffusion. The objective of this paper is to reconcile the *a priori* antagonism between the intensifying use of patent data and the pessimistic appraisal of these indicators in the academic literature. This reconciliation is done by identifying key milestones when analyzing the R&D-patent relationship at the industry level.

The empirical investigation relies on a unique panel data set composed of 18 manufacturing industries in 19 countries over the period 1987 to 2005, for which five broad patent indicators are developed. Six main methodological and policy implications summarize the major contributions of this paper.

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 stage (the extent to which additional units of R&D generate additional inventions) and a propensity-to-patent stage. This paper claims that the propensity to patent must be split into two main components in order to better understand how an increase in R&D expenditures translate into patent applications: the “appropriability propensity”, which indicates whether or not an invention is protected with patents; and the “strategic propensity”, which measures the number of patents used to protect an invention. 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 so far be gauged by measures of complexity or of patent friendliness. This theoretical insight has a major implication: Large-scale surveys such as the Community Innovation Survey in Europe should assess the two propensity components for many countries. Data on the evolution of the share of inventions that are patented as well as on the average number of patents used to protect an invention would drastically improve our understanding of the R&D-patent relationship. So far only single-country information is available for a given year or period.

Second, the econometric analysis of the patenting activity across industries, countries and over time confirm that the patent elasticity with respect to R&D is positive and significant but small. It fluctuates around 12 percent and is very robust to the patent indicator used as dependent variable (national priority filings *versus* the more restrictive and high value triadic patents). The results therefore confirm the existing dynamic time series estimates at the microeconomic level: The elasticity is much smaller than "hoped" for (Griliches, 1990) and captures only a small share of the variance in patent filings, which can be due to two important missing links unrelated to the productivity of research, namely appropriability and strategic propensities.

Third, the empirical analysis confirms that a significant productivity effect takes place and does explain part of the variations in the R&D-patent ratio, as witnessed by the positive and significant premium associated with basic research and academic research, or by the noticeable impact of the international competitiveness variable, an indicator of ultimate innovation performance. The positive impact of basic and academic research suggests that allocating more resources to university-performed research and to basic projects is a long-term policy aimed at securing the seeds of future innovations.

Fourth, the appropriability propensity plays a positive and highly significant role in the patent production function, despite the fact that its measure varies only across industries. The implicit assumption that it is similar across countries and does not vary over time is probably too strong, but there is no convincing alternative to the best of our knowledge. The strategic propensity to patent is assessed by the strength of the patent system in the inventor country and by a measure of the complexity of industries. These variables have a positive and significant impact on the propensity to patent, but probably only partially capture the strategic propensity to patent.

Fifth, the country and industry dummies allow to identify in some depth the origins of the increase in the propensity to file patents. This "dynamic propensity" is logically composed of an appropriability component and a strategic component. Two manufacturing industries, which were already characterized by a high patent-to-R&D ratio, communications and computers, turn out to be associated with the sharpest increase in the propensity to patent. This is precisely the technological area where a patent "paradox" was identified by Hall and Ziedonis (2001). In this respect our result shed some additional light on the R&D-patent relationship and its industry dimension. The pharmaceutical industry has a high appropriability propensity but is not associated with a particularly strong increase in its propensity to patent. The countries that are associated with the sharpest increase in their propensity to patent are South Korea, Poland and Spain, which witnesses a clear catching up effect. These results exemplify the pitfalls and advantages associated with patent data. Whereas they witness fundamental economic changes such as catching-up effects, they are also greatly impacted by nations' industrial structure, hence the need to improve our understanding of the "propensity" components.

Finally, the time dummies provide a broad measure of the increase in patent propensity, net of country and industry specificities, and of R&D expenditure. 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 in the unaccounted propensity to patent is observed. In other words, the "global patent warming" that is currently taking place is essentially the result of a stronger internationalization of patent applications, and not a consequence of an increased propensity to rely on patent systems with national priority applications. Innovating firms are increasingly targeting global markets and hence have a higher tendency to seek protection in regional patent offices, world-wide. This tendency would justify a stronger coordination of patent offices at the global level, provided their views on how a patent system should be designed converge noticeably.

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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 Giliches (1980)	121 US firms 1968-1875	Panel (within dimension)	0.61	Sum of log R&D (Contemporaneous + 5 lags)
Bound *et al.* (1984)	2582 firms 1976	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	OLS, Poisson and Negative Binomial	0.75-0.88	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	Nonlinear 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 firms 1973 & 1979	Cross-section; Pooled OLS	0.74	Contemporaneous log R&D
		First differences	0.4	
		3SLS	0.88	
Cincera (1997)	181 manufacturing firms 1983-1991	Panel; GEC, QGPML-gamma, Conditional Poisson, GMM	0.35-0.9	Sum of log of R&D (contemporaneous + 4 lags)
Duguet and Kabla (1998)	299 firms 1990-1992	Cross-section; Poisson Model estimated by asymptotic least squares	0.34-0.67	Log R&D
Crépon *et al.* (1998)	4164 manufacturing firms 1986-1990	Cross-section; Non-negative binomial	0.88-1.08	Patents per employee – R&D capital per employee
Blundell *et al.* (2002)	407 firms 1972-1979	Linear feedback model	0.9	Level (without individual effects)
			0.34	Within group mean scaling
Arora *et al.* (2008)	790 R&D Units 1991-1993	Cross-section; 2SLS	0.61	
Czarnitzki *et al.* (2009)	122 firms 1993-2003	Pooled cross-sectional	1.10-1.13	Log(R&D/Employment)
		Fixed effect panel	0.30-0.32	Log(R&D/Employment)
Aggregate (industry, region or country level)				
Acs and Audretsch (1988)	247 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 countries, 1973-1993	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	Cross-section of lung 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
de Rassenfosse and van Pottelsberghe (2009)	34 countries 2003	Cross-section	0.33-1.56	Log Researchers

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, wearing apparel; dressing and dyeing of fur; Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear	LOTE	3
CA	Canada	**WPAP**	20-22	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials; manufacture of paper and paper products; publishing, printing and reproduction of recorded media	LOTE	10
CH	Switzerland	**PETR**	23	Manufacture of coke, refined petroleum products and nuclear	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	14
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	1
IT	Italy	**COMP**	30	Manufacture of office, accounting and computing machinery	HTE	63
JP	Japan	**ELEC**	31	Manufacture of electrical machinery and apparatus n.e.c.	MHTE	18
KR	Korea	**COMM**	32	Manufacture of radio, television and communication equipment and apparatus	HTE	107
NL	Netherlands	**INST**	33	Manufacture of medical, precision and optical instruments, watches and clocks	HTE	22
NO	Norway	**AUTO**	34	Manufacture of motor vehicles, trailers and semi-trailers	MHTE	14
PL	Poland	**TRAN**	35	Manufacture of other transport equipment	MHTE	14
SE	Sweden	**MISC**	36	Manufacture of furniture; manufacturing n.e.c.	MHTE	
US	United States					

Note: * Based on the OECD technological classification, LOTE, MLTE, MHTE and HTE stand for low technology, medium-to-low technology, medium-to-high technology and high technology, respectively; **own industry matching based on the 'triples' data presented by von Graevenitz et al. (2008).

Table A3. Absolute and relative number of patents by country (2004)

Country	NPFCORR	%	TRIADIC	%	EPO	%	USPTO	%	REGIONAL	%
AT	2,356	0.6	284	0.6	1,259	1.2	825	0.4	1,259	0.5
BE	1,742	0.5	394	0.8	1,265	1.2	927	0.4	1,265	0.5
CA	5,569	1.5	381	0.8	1,147	1.1	3,750	1.7	3,750	1.6
CH	3,480	0.9	988	2.0	2,656	2.5	1,874	0.9	2,656	1.1
DE	49,502	13.2	6,865	13.6	24,130	23.2	17,126	7.8	24,130	10.4
DK	1,579	0.4	311	0.6	1,015	1.0	906	0.4	1,015	0.4
ES	2,525	0.7	177	0.4	886	0.9	519	0.2	886	0.4
FI	2,640	0.7	314	0.6	1,175	1.1	1,199	0.5	1,175	0.5
FR	14,635	3.9	2,675	5.3	7,839	7.5	5,541	2.5	7,839	3.4
GB	19,665	5.3	1,944	3.8	5,181	5.0	5,782	2.6	5,181	2.2
IE	559	0.1	82	0.2	237	0.2	282	0.1	237	0.1
IT	10,007	2.7	696	1.4	3,962	3.8	2,195	1.0	3,962	1.7
JP*	113,488	30.3	19,890	39.4	25,382	24.4	56,968	26.1	56,968	24.6
KR*	33,282	8.9	2,736	5.4	4,573	4.4	16,084	7.4	16,084	6.9
NL	5,742	1.5	2,329	4.6	3,879	3.7	3,362	1.5	3,879	1.7
NO	1,045	0.3	127	0.3	356	0.3	410	0.2	356	0.2
PL	2,226	0.6	13	0.0	135	0.1	99	0.0	135	0.1
SE	3,599	1.0	685	1.4	1,817	1.7	1,491	0.7	1,817	0.8
US	100,465	26.9	9,613	19.0	17,336	16.6	99,334	45.4	99,334	42.8
Total	374,106	100	50,504	100	104,230	100	218,673	100	231,927	100

Source: Own calculations

Notes: * The number of priority fillings for Japan and Korea has been divided by 3. The "%"columns report the share of each country in the total of each patent count, expressed in percent.

Table A4. Absolute and relative number of patents by industry (2004)

Industry	NPFCORR	%	TRIADIC	%	EPO	%	USPTO	%	REGIONAL	%
FOOD	7,939	2.1	997	2.0	2,172	2.1	4,156	1.9	4,258	1.8
TEXT	2,521	0.7	268	0.5	613	0.6	1,258	0.6	1,369	0.6
WPAP	4,698	1.3	605	1.2	1,324	1.3	2,418	1.1	2,649	1.1
PETR	4,632	1.2	739	1.5	1,496	1.4	2,497	1.1	2,664	1.1
CHEM	37,325	10.0	6,307	12.5	12,306	11.8	20,427	9.3	22,077	9.5
PHAR	21,229	5.7	4,872	9.6	8,762	8.4	13,831	6.3	14,734	6.4
RUBB	7,282	1.9	840	1.7	2,030	1.9	3,410	1.6	3,878	1.7
MINE	6,654	1.8	810	1.6	1,767	1.7	3,380	1.5	3,695	1.6
META	7,774	2.1	1,003	2.0	2,148	2.1	3,948	1.8	4,319	1.9
FABM	10,142	2.7	925	1.8	2,579	2.5	4,532	2.1	5,239	2.3
MACH	44,986	12.0	4,741	9.4	11,938	11.5	22,169	10.1	24,578	10.6
COMP	53,304	14.2	7,012	13.9	12,922	12.4	36,830	16.8	37,443	16.1
ELEC	14,209	3.8	1,794	3.6	3,736	3.6	8,527	3.9	9,016	3.9
COMM	81,450	21.8	11,453	22.7	21,622	20.7	55,051	25.2	56,313	24.3
INST	15,260	4.1	2,148	4.3	4,211	4.0	9,400	4.3	9,821	4.2
AUTO	34,274	9.2	4,088	8.1	9,983	9.6	16,838	7.7	18,995	8.2
TRAN	10,916	2.9	1,329	2.6	3,112	3.0	5,893	2.7	6,441	2.8
MISC	9,511	2.5	573	1.1	1,510	1.4	4,107	1.9	4,439	1.9
Total	374,106	100	50,504	100	104,230	100	218,673	100	231,927	100

Source: Own calculations

Note: The "%"columns report the share of each industry in the total of each patent count.

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

Δ log(#patents)	NPFCORR (1)	TRIADIC (2)	REGIONAL (3)
Δ log(R&D)	0.019	-0.004	0.020
	(0.013)	(0.029)	(0.018)
Δ SHARE BASIC	0.016***	-0.0002	-0.005
	(0.003)	(0.007)	(0.004)
log(#patents) (t-1)	-0.114***	-0.365***	-0.192***
	(0.011)	(0.019)	(0.014)
log(R&D) (t-1)	0.016***	0.041***	0.022***
	(0.005)	(0.011)	(0.007)
SHARE BASIC (t-1)	0.019***	0.029***	0.023***
	(0.003)	(0.006)	(0.004)
Countries dummies	Yes ***	Yes ***	Yes ***
Industry dummies	Yes ***	Yes ***	Yes ***
Time dummies	Yes ***	Yes ***	Yes ***
Number of observations	1811	1811	1811
Adjusted R-Squared	0.331	0.241	0.170
Long-run impact of R&D	0.140***	0.112***	0.115***
Long-run impact of SB	0.167***	0.079***	0.120***

Notes: Standard errors in parentheses; ***, **, * denote significance at the 1, 5 and 10-percent levels, respectively. The rows "country dummies", "industry dummies" and "time dummies" report the significance level of the joint effect of theses dummies.

Appendix 2. Panel unit root and cointegration tests

In order to analyse the dynamics of the R&D-patent relationship within an ECM framework, one need to test whether the variables have a unit root and are cointegrated. Three tests on unit roots in panel data are implemented: Levin, Li and Chu (2002); Im, Pesaran and Shin (2003) and a Fisher type test (Choi, 2001); denoted respectively LLC, IPS and Fisher in Table A6. The three tests are devised under the null hypothesis that all the variables in the panel have a unit root. LLC assumes that all individuals have the same autoregressive parameter whereas IPS and Fisher allow both for heterogeneous roots and for heterogeneous presence of a unit root. Since some of these tests require a strongly balanced panel, they were performed on a restricted sample of our initial panel data set (this restriction was simply based on the availability of data to obtain the largest possible balanced panel, which means going from 4937 to 2516 observations).

Table A6. Panel unit root tests

P-values	NPFCORR	TRIADIC	REGIONAL	EPO	USPTO	R&D
LLC	1	1	1	1	1	1
IPS	0.787	0.635	0.999	1	0.283	0.08
Fisher	0.872	0.806	1	1	0.368	0.091

Notes: Specifying one-year lag structure in the regressions performed in computing the test statistics. LLC: no panel-specific mean included. IPS: panel-specific mean included, subtracting the cross-sectional averages 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, subtracting the cross-sectional averages from the series.

It appears that most of these tests allow us to reject the null hypothesis of a unit root; the series are therefore non-stationary. Concerning the cointegration, 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 that there is evidence of cointegration for at least one of the cross-sectional units. The second pair (denoted P) formulate the alternative such that a rejection of the null should be taken as a evidence of cointegration for the panel as a whole.

Table A7. Panel cointegration tests

P-values	NPFCORR	TRIADIC	REGIONAL	EPO	USPTO
Gt	0	0	0.067	0.998	0.028
Ga	0	0	0.224	0.967	0.098
Pt	0	0	0.25	0.941	0.016
Pa	0	0	0.026	0.435	0.001

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 cointegration 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 there exists a long-run equilibrium level between the number of patents and R&D efforts.

Appendix 3. Construction of the dynamic propensities

The variables presented in Figures 6, 7 and 8 are based on ψ_i, ψ_i and ψ_t in Equation (8) that is, the country, industry and time-effects, respectively. Since the dependent variable is the difference of the log of patent filings, the fixed effects can be interpreted as the growth rate in propensity to patent taking into account all the potential explanatory variables. We refer to these parameters as the dynamic propensities.

Note that the fixed effects cannot be recovered immediately from Equation (8). Indeed, the fact that the error correction term is left open in Equation (8) 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 6, 7 and 8 have been recovered in the following way. We have first estimated the residuals from Equation (4) and injected them into Equation (8) in lieu of the lagged long-term relationship (the expression in parentheses in Equation (8)). The fixed effects of this modified specification can be interpreted as the country, industry and time components of the change in the propensity to patent. Figures 6 and 7 respectively present the parameters ψ_j and ψ_i, which are normalized to lie between 0 and 1 for ease of readability. Figure 8 presents the cumulative effect of the time dummies on patent counts, including the average industry effect, the average country effect and the constant.