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The More You Spend, the More You Get? The Effects of R&D and Capital Expenditures on the Patenting Activities of Biotechnology Firms

Roberta Piergiovanni, Enrico Santarelli

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The authors of this paper are Roberta Piergiovanni (Istat-Ufficio Regionale per l'Emilia-Romagna) and Enrico Santarelli (University of Bologna, Department of Economics and European Commission - JRC, Institute for Prospective Technological Studies). Previous versions have been presented at CONCORD 2010 – Conference on Corporate R&D (Seville, 3-4 March 2010), and at the Workshop on "The Output of R&D Activities: Harnessing the Power of Patents Data – II" (Seville, 27-28 May 2010). The work has benefited from the comments by Francesco Bogliacino, Michele Cincera, Pietro Moncada-Paternò-Castello, Vincenzo Spiezia, Alessandro Sterlacchini, Marco Vivarelli, and two anonymous referees.

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Contact information: F. Hervás
European Commission, Joint Research Centre - Institute for Prospective Technological Studies
Edificio Expo
C/ Inca Garcilaso, 3
E-41092 Seville (Spain)
Fax: +34 95 448 83 26; E-mail: jrc-ipts-kfg-secretariat@ec.europa.eu
IPTS website: http://ipts.jrc.ec.europa.eu/; JRC website: http://www.jrc.ec.europa.eu
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Abstract

This paper provides evidence on the mechanisms influencing the patent output of a sample of biotechnology firms from the input of *indirect* knowledge acquired from capital expenditures and *direct* knowledge from in-house R&D. Statistical models of counts are used to analyse the relationship between patent applications and R&D investment and capital expenditures. It focuses on biotechnology in the period 2002-2007 and is based on a unique data set drawn from various sources including the *EU Industrial R&D Investment Scoreboard*, the European Patent Office (EPO), the US Patent and Trademark Office (USPTO), and the World Intellectual Property Organisation (WIPO/PCT).

The statistical models employed in the paper are Poisson distribution generalisations with the actual distribution of patent counts fitting the negative binomial distribution and gamma distribution very well.

Findings support the idea that capital expenditures – taken as equivalent to technological change embodied in new machinery and capital equipment - may also play a crucial role in the development of new patentable items from scientific companies. For EPO patents, this role appears even more important than that played by R&D investment.

The overall picture emerging from our analysis of the determinants of patenting in biotechnology is that the innovation process involves a well balanced combination of inputs from both R&D and new machinery and capital equipment.

JEL Classification: L25; L65; O34

Keywords: Patents; R&D; Capital expenditure; Poisson models; Biotechnology

1 Introduction

According to Pavitt (1984), in-house R&D is the main determinant of the innovative output of science-based firms. However, this does not exclude other factors from playing an important role. For example, Arora et al. (2008) found that the effectiveness of a company's patent strategy in U.S. biotechnology was determined by the level of its R&D effort and ultimately its ability to innovate. However, Hall and Ziedonis (2001) showed that both in-house R&D *and* capital expenditures exerted a positive impact on the innovative output of US semiconductor companies.

This paper provides evidence on the mechanisms influencing the patent output of a sample of biotechnology firms from the input of *indirect* knowledge acquired from capital expenditures and *direct* knowledge from in-house R&D. In fact, whereas the study of the impact of current and past R&D investment on patenting is a standard exercise in the innovation literature on science-based firms, only scant attention is paid to that of capital expenditures. Following the well-known controversy between Dale Jorgenson and Robert Solow in the 1960s (on which see Hercowitz, 1998), the role of capital expenditures since then has been mostly considered either by studies on the determinants of productivity growth[1] or on the innovative activities of low- and medium-technology industries, characterised by the widespread presence of small firms (Santarelli and Sterlacchini, 1990 and 1994; Santamaría et al., 2009).[2]

Nevertheless, in the tradition of Terleckyj (1984) and in light of the results by Hall and Ziedonis (2001), one may assume that capital expenditures also influence the innovative output of science-based firms. We test this hypothesis in relation to the patent output of biotechnology firms, which has been shown by previous studies to depend crucially on developments arising from basic scientific research (Patel et al., 2008).

The rest of this paper is organised as follows: Section 2 explains the choice of biotechnology as a field of analysis; Section 3 presents the data, prepared from various sources, to obtain a new and unique dataset; Section 4 introduces variables and models, besides discussing some estimation problems arising from the analysis of events involving non-negative integer counts, as is the case with patents; Section 5 presents and discusses the estimation results; then

[1] Under the assumption that external or "used" R&D is mainly embodied in intermediate and capital goods (Terleckyj, 1974).
[2] Under the assumption that, for such companies, most innovations come from suppliers of machinery and capital equipment (Pavitt, 1984).

finally, Section 6 summarises the main results and offers suggestions for company strategy and innovation policy.

2 Why biotechnology?

The choice of biotechnology as a test for the hypothesis that both capital expenditures and R&D investment are determinants of innovation in a high-tech industry depends on a series of obvious and not-so-obvious reasons. Among the obvious, is the fact that nowadays it represents probably the most typical science-based sectoral aggregate in Pavitt's (1984) terms. Among the not-so-obvious, are its composite, multidisciplinary and versatile nature. Biotechnology is highly *composite*, in that it includes the agricultural (in turn, subdivided into plant and animal cell technologies), medical, microbial and marine biotechnology fields. It is *multidisciplinary* from both a scientific and a technological perspective. It encompasses molecular biology, biochemistry, genetics, genomics, bioinformatics and environmental sciences on the one hand; and recombinant DNA technology, gene transfer, embryo manipulation and transfer, monoclonal antibody production, and bioprocess engineering on the other. It is very *versatile*; encompassing industries such as pharmaceuticals, food, agriculture, energy and chemicals. It is also used in a number of industrial applications and in the development of a variety of products: biopharmaceuticals, vaccines, industrial enzymes, biological pesticides, crop seeds, bio-reagents, DNA chips, DNA analysis tests, medical diagnostic kits, nutritional supplements, among others. Therefore, more than just a full industrial sector in itself biotechnology is "a hybrid form of an industry" (Roijakkers and Hagedoorn, 2003. p. 64) or "a set of technologies with applications in a number of different sectors" (Patel et al., 2008. p. i).

Another reason for choosing biotechnology is that it is far from new. For centuries, genetic modification of living organisms has been obtained by means of selective breeding, and microbes have been used for the fermentation processes involved in producing bread, alcohol and cheese. What is new, and has given rise to the myth of a 'biotech revolution,' are the tools that scientists use nowadays, enabling them to alter an organism's DNA with much greater precision than in the past. Therefore, if one follows an 'object approach' (Archibugi, Evangelista and Simonetti, 1994), biotechnology can be seen as being part of a model of technological change in which product innovation, often of a sequential and complementary nature, is driven by process innovation, in turn made possible by investment in new machinery and capital equipment.

Biotechnology is not a technological paradigm in the sense of Dosi (1982), but rather the vehicle of a "de-maturity" process in the sense of Utterback and Abernathy (1975), within which R&D and capital expenditures pave the way for new applications of biotechnology itself (Orsenigo, 1989; Arora and Gambardella, 1990; Gambardella, 1995; McKelvey et al., 2005; Nesta and Saviotti, 2006; Santarelli and Lotti, 2008; Wonglimpiyarat, 2008). In fact, no truly convincing empirical evidence has so far been provided of a biotech revolution able to bring about economic development as a result of improvements, in the drug discovery process and in healthcare (Nightingale and Martin, 2004; Hopkins et al., 2007), among other areas. Following the path of other 'general purpose engines', such as the electric dynamo at the end of the Second Industrial Revolution (David, 1990), it is likely that the expansion of medicinal biotechnology into a number of areas will take much longer than originally expected, along with the achievement of complementary technological and organisational changes (David, 1990; von Tunzelmann, 1993). Networks involving newly founded biotechnological firms and large pharmaceutical firms should earlier or later turn new knowledge into innovations (Hagedoorn, 2002; Roijakkers and Hagedoorn, 2006). Meanwhile, many over-optimistic expectations will have to be revised; and the substantial changes which have already occurred in the biological sciences and in the organisation of R&D field, must be given time to result in significantly improved or entirely new commercial products (Nightingale and Martin, 2004). However, it should be remembered that most medical innovation is incremental, and major breakthroughs following R&D investment arrive in a haphazard fashion. From a theoretical viewpoint, this finding raises doubts about the assumption of constant returns to scale in R&D (Pakes and Griliches, 1980; Hausman et al, 1984; Griliches, 1990; Hall and Mairesse, 1995; Crepon and Duguet, 1997; Cincera, 1997; Blundell et al., 2002; Bogliacino and Naranjo Ramos, 2008), and must therefore be subjected to further investigation. From an empirical viewpoint, it would bring forth the spectre of anticipated technological exhaustion and a vicious circle where lower innovative output reduces both the private return from R&D and the equilibrium level of R&D investment (Lanjouw and Schankerman, 2004).

In the overall biotechnology innovation process, it is likely that investment in new capital equipment or upgrading of existing equipment is an adjunct to R&D expenditure. In fact, if one applies to this subject the more general considerations raised by Greenwood and Yorukoglu (1997, p 49), one may argue that the last decade has represented an "era of rapid investment-specific technological progress" in the evolution of biotechnology, which makes embodied technological change crucial for making the overall innovation process more focused.

3 Data and summary statistics

Created in response to the European Commission's Research Investment Action Plan, and currently part of the Industrial Research Monitoring Activity carried out jointly by the Joint Research Centre (JRC) and the Research (DG RTD) Directorates-General of the European Commission, the *EU Industrial R&D Investment Scoreboard* (the *Scoreboard*) provides information on the 1000 EU and 1000 non-EU listed and non-listed companies that invested the largest sums in R&D in the previous reporting year.[3] It is taken from a database containing information from audited company annual reports and accounts. The R&D considered for the *Scoreboard* is investment directly funded by the companies themselves, excluding R&D performed under contract for customers, such as governments or other companies (either independent or associated). Since most available accounts do not specify where R&D is actually performed, the *Scoreboard* attributes each company's total R&D investment to the country in which the company has its registered office. The *Scoreboard* also provides data on company capital expenditures to acquire or upgrade physical assets such as equipment, property and industrial buildings. In company accounts, capital expenditures are added to the asset account (i.e., capitalised), thus increasing the asset's base, and are disclosed as additions to tangible fixed assets.

The *Scoreboard* does not collect patent information. Therefore, being aware that firms may choose from many different patenting routes, we performed a manual name-matching procedure[4] (by applicant name) for patent applications with the European Patent Office (EPO), the US Patents and Trademark Office (USPTO), and the *WIPO/PCT Patents Fulltext* database, published under the auspices of the World Intellectual Property Organisation (WIPO).[5] The decision to collect patent data from these three sources is motivated by *a)* their coverage of a large fraction of total patenting activities, which renders each of them useful for

[3] The first two releases of the *Scoreboard*, in 2004 and 2005 dealt with the top 500 and top 700 EU and the top 500 and top 700 non-EU companies, respectively.

[4] Matching patent datasets with a list of company names, or playing the "names game" as aptly called by Melamed et al. (2006), is a preliminary and controversial step in the assessment of organisations' patent portfolios. Nevertheless, given the relatively small number of cases, we maintain that the potential problem of reliability has been substantially alleviated by our manual procedure. Since addressing this issue is beyond the scope of our paper, we refer to Melamed et al. (2006), Thoma and Torrisi (2007), Raffo and Lhuilleri (2009), and Thursby et al. (2009) among others for more in-depth discussion and proposals for alternative procedures.

[5] Being aware of the advantages and disadvantages of the use of patent-based innovation output indicators (Santarelli and Piergiovanni, 1996), in this study we rely upon the assumption of homogeneity of technological content and economic significance of patents within the same technological field. Heterogeneity is conversely assumed to arise from the choice of one or multiple patent institutions.

international comparisons; *b)* the nevertheless marked differences among them in terms of bureaucratic procedures, enforcement, technological and market value of patent applications.

EPO patents have been shown to be high quality patents with high private value (Deng, 2007), at least in comparison with national patents. Therefore, they also represent a viable option for Small and Medium Sized Enterprises (SMEs) pursuing aggressive innovation strategies. Their main shortcoming is that on average they are more expensive than patents from other institutions, due to high costs coming from translations attached to country extension. Besides, one has to take into account that they do not result in a 'truly European' patent system, since the harmonisation process concludes when the patent is granted, whereas the legal implications of enforcement still differ among countries (Santarelli and Lotti, 2008).

Reform of the opposition system in 1982 and transformation of the USPTO into a service agency in 1990 have conversely made the entire patenting procedure in the US more "user-friendly" and perhaps less selective, leading to a proliferation of low-quality patents (Jaffe and Lerner, 2004). In effect, creation of a centralised appellate court (CAFC, Court of Appeals for the Federal Circuit) for adjudicating formal disputes involving patents has given rise to an enforcement mechanism that is highly sympathetic to the views of patent holders. By systematically endorsing the exclusionary rights of patent holders, the court has therefore strengthened US patent rights, ultimately favouring a pro-patent shift for innovative activities.[6,7]

Operated by WIPO, the Patent Cooperation Treaty (PCT) establishes a centralised patent application system, but does not grant patents. Available since 1978, it covers 177 states participating in the Patent Cooperation Treaty. Applications with WIPO are a first step in the process of international application, eventually leading to the grant of patent protection in any state party of this treaty. Accordingly, the PCT route can be used for strategic reasons to gain time with respect to competitors before the patent is applied, in particular, in relation to inventions of a high perceived value which are expected to generate a cluster of patents.

Deliberate exclusion of the national Intellectual Property filings implies that we are paying less attention to patenting by the least technologically advanced fraction of SMEs. However,

[6] It has to be considered that both the EPO and USPTO publish all patent applications 18 months after their filing date. However, the USPTO does not publish applications which have been withdrawn or filed with a non-publication request, stating that the application is US only.

[7] Because the US is the world's leading country for the commercial development of biotechnology, companies have a strong incentive to apply for patent protection with the USPTO.

provided that we are using R&D data for the top R&D investors, we believe that this choice does not represent a drawback in our analysis.[8] Because companies may or may not be included in subsequent releases of the *Scoreboard*, we have an unbalanced panel with a minimum of 97 (in 2002) and a maximum of 123 (in 2007) companies in each of the 6 years.[9] Since we cannot exclude double counting of patents applied to different patent offices, the empirical analysis is performed for each of the three types of source separately.

The descriptive statistics about patent applications by the biotechnology firms included in the *Scoreboard* during the period 2002-2007 are presented in Table 1. They show that EPO patents are more homogeneously distributed across companies than the other two types of patents, as suggested by the low value of the standard deviation, with an average of just three per company over the period. As the companies in our database are those investing the largest sums in biotech R&D, it has to be expected that most of them possess both manufacturing and research capabilities. This suggests that they might tend to rely on both capital equipment and patents to recoup investments in R&D. Accordingly, they should be characterised by a large number of patent applications and heavy investments in both R&D and capital equipment. In fact, Table 2 shows that average expenditures on R&D grow almost monotonically over time (from 65.5 in 2002 to 73.5 in 2007 million €), whereas capital expenditures display a more erratic pattern (with a trough in 2007).

Table 3 shows that about 50 per cent of companies have more than 250 employees, with one third exceeding the threshold of 500 employees. These are likely to be diversified firms which perform R&D in a variety of fields, *including* biotechnology, and which are also endowed with manufacturing capabilities. Conversely, some of the 13% percent of companies that are shown in Table 3 to have fewer than 50 employees are probably research labs devoid of manufacturing capabilities, or Dedicated Biotechnology Firms (DBFs) with biotechnology as their core business, which either explore new innovation opportunities directly or provide specialised research services to incumbents.[10]

[8] Another important source, the Japanese Patent Office (JPO), has also been excluded. With the JPO, each claim beyond the first requires additional official fees for substantive examination and maintenance. As a consequence of the additional fees, Japanese patents tend to average fewer claims than EPO and USPTO patents. As a result, this system has been seen to encourage numerous filings of narrow claims that build incrementally on fundamental technologies developed by domestic and foreign inventors (Maskus and McDaniel, 1999). Thus, for the sake of procedural homogeneity, we decided not to use patent applications with JPO.

[9] According to a detailed report on biotechnology in eighteen European countries and the U.S. (Critical I, 2006), at the end of 2004 the total number of companies in business was 4,154. Thus, the representativeness of our sample with respect to the population of biotech firms in such countries is below 3.0%.

[10] According to OECD (2009), DBFs are firms whose predominant activity involves the application of biotechnology techniques to produce goods or services and/or to perform biotechnology R&D.

Table 1 – Summary statistics for patent applications (2002-2007)

Size class	Firms		Patents		Mean	St. dev.
	Number	percent	number	percent		
EPO patents						
0 [min]	250	38.6	0	0.0		
1-3 (min-mean]	210	32.4	364	16.1	1.7	0.8
4-7 (mean-st.dev.]	110	17.0	563	25.0	5.1	1.1
8-95 (st.dev.-max]	78	12.0	1,328	58.9	17	15.2
Total	648	100.0	2,255	100.0	3.5	7.5
USPTO patents						
0 [min]	139	21.1	0	0.0		
1-10 (min-mean]	327	49.5	1,212	19.1	3.7	2.6
11-15 (mean-st.dev.]	75	11.4	910	14.3	12.1	1.8
16-99 (st.dev.-max]	119	18.0	4,225	66.6	35.5	20.8
Total	660	100.0	6,347	100.0	9.6	15.5
WIPO patents						
0 [min]	99	15.1	0	0.0		
1-11 (min-mean]	377	57.6	1,598	22.5	4.2	2.7
12-18 (mean-st.dev.]	69	10.6	948	13.3	13.7	2.1
19-164 (st.dev.-max]	109	16.7	4,564	64.2	41.9	27.9
Total	654	100.0	7,110	100.0	10.9	18.4

Table 2 – Summary statistics for company-specific characteristics

Variable: employees					
Year	Obs	Mean	Std. Dev.	Min	Max
2002	97	947.5	1,749.5	5	10,118
2003	103	957.7	1,897.5	5	12,900
2004	108	1,047.7	2,109.8	6	14,400
2005	110	1,073.8	2,200.1	11	16,500
2006	109	1,140.2	2,482.9	12	20,100
2007	123	985.8	2,248.3	12	17,500
Variable: capital expenditures					
Year	Obs	Mean	Std. Dev.	Min	Max
2002	104	27.9	71.3	0.0	627.3
2003	108	28.1	109.3	0.0	1,075.5
2004	108	25.2	99.8	0.0	983.3
2005	110	24.6	78.8	0.0	735.0
2006	102	32.7	85.5	0.0	750.0
2007	94	22.3	44.1	1.0	300.0
Variable: R&D expenditures					
Year	Obs	Mean	Std. Dev.	Min	Max
2002	104	65.5	123.5	0.2	1,064
2003	108	62.2	139.1	0.3	1,312
2004	109	68.7	162.3	0.4	1,492
2005	111	84.1	206.6	2.8	1,962
2006	110	88.0	254.9	3.4	2,553
2007	128	73.5	210.5	4.4	2,234

Monetary values are expressed in m €; employment in number of employees.

Whereas diversified companies can be expected to invest heavily in new machinery and capital equipment, since the supply chain of the biotechnology system relies upon the contribution of producers of components and manufacturing devices (Tassey, 2010), DBFs should have R&D expenditures as their only source of new knowledge and may not exploit

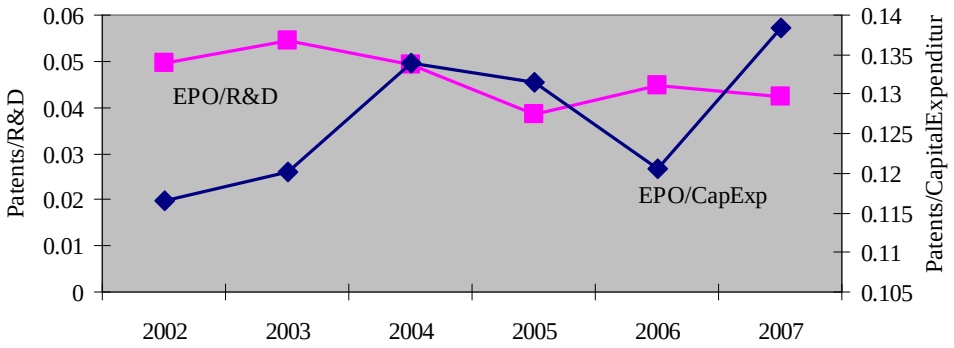
their patented inventions directly. This is confirmed by the fact that many of them have been found to sell the rights to exploit their patents to other companies (Patel et al., 2008).[11] In effect, in our sample firms that made no capital expenditures over the entire period and with less than 50 employees represent 48.7% of the total.[12]

Table 3 – Number of firms by employment size class and year

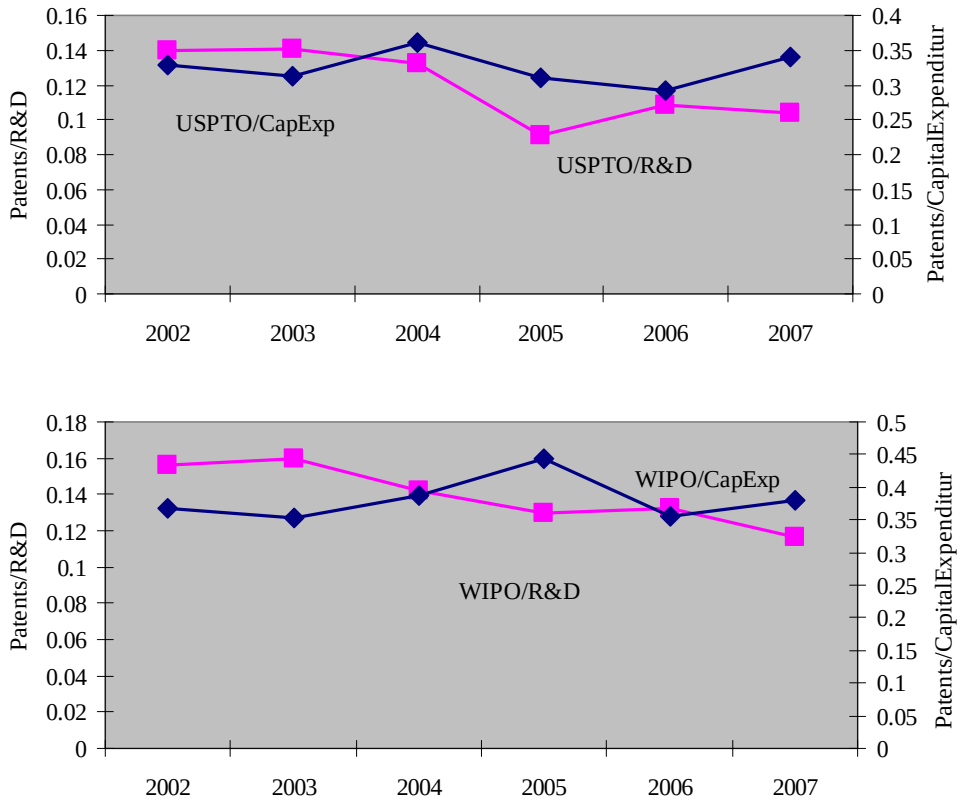
	1-49	50-249	250-499	500 and more	Total
2002	13	35	16	33	97
2003	12	37	21	33	103
2004	12	42	18	36	108
2005	11	43	15	41	110
2006	15	35	18	41	109
2007	15	48	18	42	123

By keeping the three sources of patent data separate, in Figure 1 we show the patent/R&D and patent/capital expenditures ratio for all the biotech firms in the sample. The two ratios follow different trends: whereas the patent/R&D ratio turns out to be (slightly) decreasing over time for each type of patent, the patent/capital expenditures one, although exhibiting a more erratic pattern, is (slightly) increasing.[13]

Figure 1 - Number of patent applications on R&D and Capital Expenditure



[11] In such a case, it is of course unlikely that DBFs invest heavily in new machinery and capital equipment.
[12] This explains the minimum values of zero found for capital expenditure between 2002 and 2006.
[13] Nevertheless, it has to be noticed that the number of patent applications is increasing over time. These figures may also reflect the fact that the monetary figures provided by the *Scoreboard* are not deflated, but simply converted in €.



4 Model specification

To detect whether R&D investment, capital expenditures and company-specific characteristics have affected the production of new inventive output from the top R&D investors in biotechnology over the period 2002-2007, we used various procedures apart from the usual OLS one[14]. These were all based on a generalised linear model (GLM), which extends the traditional linear model to a wider range of data analysis problems, by using a function to link the mean expected response to a linear function of the explanatory variables. For the probability distribution of the dependent variable we assume three distributions: the Poisson distribution, the negative binomial distribution introduced by Greenwood and Yule (1922), and the gamma distribution. In our specifications of a patent equation, in itself an empirical counterpart of the knowledge production function model originally put forward by Griliches (1979; see Crepon and Duguet, 1997), $Pat_{i,t}$ is the number of patent applications by company

[14] It is worth recalling that the regression cannot be linear with count variables. The problem of nonlinearity is handled through nonlinear functions that transform the expected value of the count variable into a linear function, of the explanatory variables. Such transformations are referred to as link functions.

i in year *t*; $\alpha_{i,t}$ are fixed effects for two company types (European and non-European)[15], and $z_{i,t}$ are time fixed effects captured by a time trend. The other independent variables are our company-specific variables - i.e., in-house R&D[16] and its lagged (by 1 and 2 years) and squared values, capital expenditures[17] and its lagged (by 1 and 2 years) and squared values, employment size[18] - and a dummy variable $D(n_{i,t}=0)_{i,t}$ added when $n_{i,t}$= 0. Finally, an error term was included:

$$1) \quad Pat_{i,t} = \alpha_{i,t} + z_{i,t} + D(n_{i,t}=0) + \beta_1 \ln RD_{i,t} + \beta_2 \ln RD_{i,t-1} + \beta_3 \ln RD_{i,t-2} + \beta_4 (\ln RD_{i,t})^2 + \chi_1 \ln CapExp_{i,t} + \chi_2 \ln CapExp_{i,t-1t} + \chi_3 \ln CapExp_{i,t-2t} + \chi_4 (\ln CapExp_{i,t})^2 + \delta \ln Emp_{i,t} + u_{i,t}^{Pat}$$

The distribution of patent applications with each of the three sources used (EPO, USPTO, and WIPO) is highly skewed to the right, and this renders the OLS specification (1) inappropriate. Besides, in view of the fact that our dependent variable is a count of the total number of patents applied for by a particular firm in a given year, statistical models for non-negative integers are the most appropriate analytical tools. Thus, we tried with different applications and generalisations for the Poisson distribution. In particular, the count of patents applied for at EPO, USPTO and WIPO/PCT by biotechnology firms included in our sample was analysed by estimating the following specification, in which the probability of observing $y_{i,t}$ patents given a certain set of right-hand-side variables is equal to:

$$2) \quad \Pr(Y_{i,t} = y_{i,t} \mid \lambda_i) = \frac{e^{-\lambda_{i,t}} \lambda_{i,t}^{y_{i,t}}}{y_{i,t}!} \qquad \text{for } y = 0, 1, 2, \ldots$$

where λ_i is the mean equal to the variance with *i* indexing firms and *t* time; letting the mean depend on a vector of explanatory variables $\mathbf{x}_i$ we have a simple linear model of the form:

[15] For the purposes of the *Scoreboard*, companies are allocated to the country of their registered office, which sometimes can be different from their operational or R&D headquarters. The main implication is that company location is independent of the actual location of its R&D activity. Use of this dummy variable is particularly important to take into account the fact that, in the US and other countries, it is common practice to include engineering costs relating to product innovation in R&D expenditures. These engineering costs have been excluded from the *Scoreboard* only if they have been disclosed separately. Accordingly, an overstatement of some overseas R&D investment figures in comparison with the EU is possible.

[16] Defined, consistent with the OECD "Frascati" Manual ("Guidelines for the collection of R&D data"), as the cash investment funded by the companies themselves.

[17] Defined as "expenditure used by a company to acquire or upgrade physical assets such as equipment, property, industrial buildings."

[18] Defined as the total number of consolidated average employees, or year-end employees if average not stated.

$$\lambda = \mathbf{x}_i \boldsymbol{\beta},$$

but with the disadvantage that the linear predictor on the right hand side can assume any real value, whereas the Poisson mean on the left hand side, which represents an expected count, has to be non-negative. The solution to this problem is to model the logarithm of the mean and assume that the transformed mean follows a linear model:

$$\ln(\lambda_i) = \mathbf{x}_i \boldsymbol{\beta}.$$

In this model, the regression coefficient β represents the expected change in the logarithm of the mean per unit change in the predictor x_i. Exponentiating the previous equation we obtain:

$$\lambda_i = e^{x_i \beta}$$

Increasing x_i by one unit multiplies the mean by a factor e^{β}. Finally, the model becomes:

$$f(y) = \frac{e^{-e^{x\beta}} e^{(x\beta)y}}{y!}$$

The Poisson model is estimated using the maximum-likelihood function for equation (2):

$$L = \prod_{i=1}^{n} \frac{e^{-\lambda_{i,t}} \lambda_{i,t}^{y_{i,t}}}{y_{i,t}!}$$

Taking the logarithm and summing over observations, the log likelihood is given by:

$$3) \quad \log(L) = \sum_i \{[y_i \ln(\lambda_i) - \lambda_i] - \ln(y_i!)\}$$

where $\ln(y_i!)$ is a constant.

As shown by Crepon and Duguet (1997, p. 245), the basic Poisson model has various weaknesses. In fact, it does not allow for individual effects possibly correlated with the independent variables. It assumes that the independent variables are exogenous and, finally, it does not allow for serial correlation of the residuals. In addition, the Poisson regression restricts the response variable to having a mean equal to its variance. If this assumption is violated, the resulting estimates are consistent, whereas those of the variance are not. It can result in spuriously small standard errors (biased downwards) of the estimates, with these inconsistent variance estimates invalidating any hypothesis testing. Thus, in practice the Poisson regression model rarely fits due to overdispersion (Maddala, 1983; Lang, 1997; Cameron and Trivedi, 1998). To evaluate the adequacy of the Poisson specification (2) we perform a goodness-of-fit test of the model (therefore turning to an investigation of the residuals), finding large values of the chi^2 test (1441.33 for EPO; 2409.59 for USPTO; 2466.77

for WIPO), which indicate that this model is inappropriate. In addition, the values for the deviance and the Pearson χ^2 dispersion indicate that there is overdispersion (larger than 1). Consequently, the confidence intervals are likely to be too narrow. McCullagh and Nelder (1989) use the Pearson χ^2 dispersion divided by the degrees of freedom to estimate the scale parameter for the quasi-likelihood method for Poisson models. Allowing for overdispersion has no effect on the regression coefficients, but a large effect on the p-*values* and confidence intervals. However, the greater sampling variability required results in a loss of efficiency of the coefficients.

In accordance with the results of the above tests, we ran a generalised linear model (GLM) (model III in Tables 4-5) with the Poisson probability distribution and a log link function. To deal with the overdispersion issue, which in our case is not due to a greater than expected incidence of zero counts, we scaled the standard errors by using the square root of the Pearson χ^2 dispersion. With this procedure, the coefficients are identical to those obtained with the previous estimate, but the standard errors are adjusted to compensate for overdispersion in the Poisson distribution (Heinzl and Mittlböck, 2003).

An alternative to scaling the standard errors would be to use a different distribution than the Poisson distribution, which would allow for the variance to be greater than the mean. We therefore analysed the data with a negative binomial distribution (model IV in Tables 4, 5 and 6 below) (Greenwood and Yule, 1920; Agresti, 2002), assuming that the dependent variable is overdispersed and does not have an excessive number of zeroes.[19]

The negative binomial model is a generalisation of the Poisson regression model, where an unobserved heterogeneity term for observation *i* is introduced and assumed to follow a gamma distribution. Thus, the patent counts are assumed to differ randomly in a manner that is not fully accounted for by the observed variables ($\mathbf{x}_i$). This is formulated as:

$$\mu_i \tau_i = e^{x_i \beta + \varepsilon_i}$$

Where the unobserved heterogeneity term $\tau_i = e^{\varepsilon_i}$ is independent of the regressor vector $\mathbf{x}_i$. Then the distribution of y_i conditional on $\mathbf{x}_i$ and τ_i is the Poisson conditional mean and conditional variance $\mu_i \tau_i$:

[19] As in fact is the case with each of the three patent counts.

$$4)\ \Pr(Y_{i,t} = y_{i,t} \mid \mathbf{x}_i, \tau_i) = f(y_{i,t} \mid \mathbf{x}_i, \tau_i) = \frac{e^{-\mu_i \tau_i}(\mu_i \tau_i)^{y_{i,t}}}{y_{i,t}!} \qquad \text{for } y = 0, 1, 2, \ldots$$

Let $g(\tau_i)$ be the probability density function of τ_i, then the distribution is obtained by integrating with respect to τ_i:

$$5)\ f(y_{i,t} \mid \mathbf{x}_i) = \int_0^\infty f(y_{i,t} \mid \mathbf{x}_i, \tau_i) g(\tau_i) d\tau_i$$

A solution to this integral exists when τ_i is assumed to follow a gamma distribution with a mean of 1 and a variance equal to 1/k:

$$g(\tau_i) = \frac{k^k}{\Gamma(k)} \tau_i^{k-1} e^{-k\tau_i}$$

Finally, resolving the (5) and using the following gamma function:

$$\Gamma(x) = \int_0^\infty z^{x-1} e^{-z} dz$$

we obtain the negative binomial model:

$$6)\ f(y_i \mid \mathbf{x}_i) = \frac{\Gamma(y_{i,t} + k_{i,t})}{y_{i,t}!\,\Gamma(k_{i,t})} \left(\frac{k_{i,t}}{k_{i,t} + \mu_{i,t}}\right)^{k_{i,t}} \left(\frac{\mu_{i,t}}{k_{i,t} + \mu_{i,t}}\right)^{y_{i,t}}$$

With y_i=0,1,2,… and where $\frac{1}{k} = \alpha$, determines the degree of dispersion, Γ is the gamma probability distribution, and the variance is $\mathrm{Var} = \mu + \frac{\mu^2}{k} = \mu + \alpha\mu^2$, when α increases the variance of the negative binomial distribution also increases.

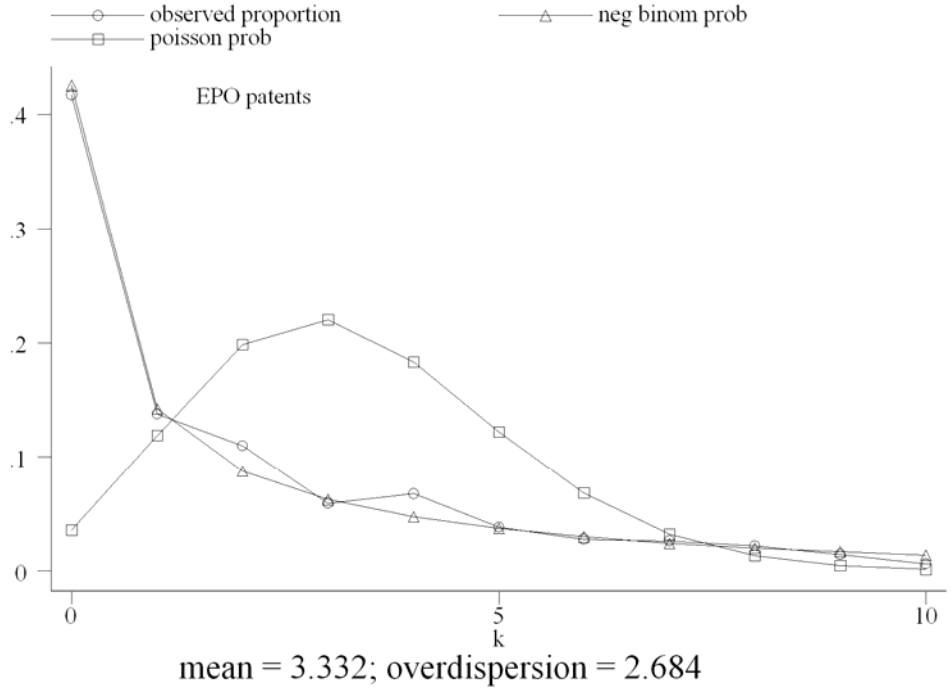
The log-likelihood function is given by:

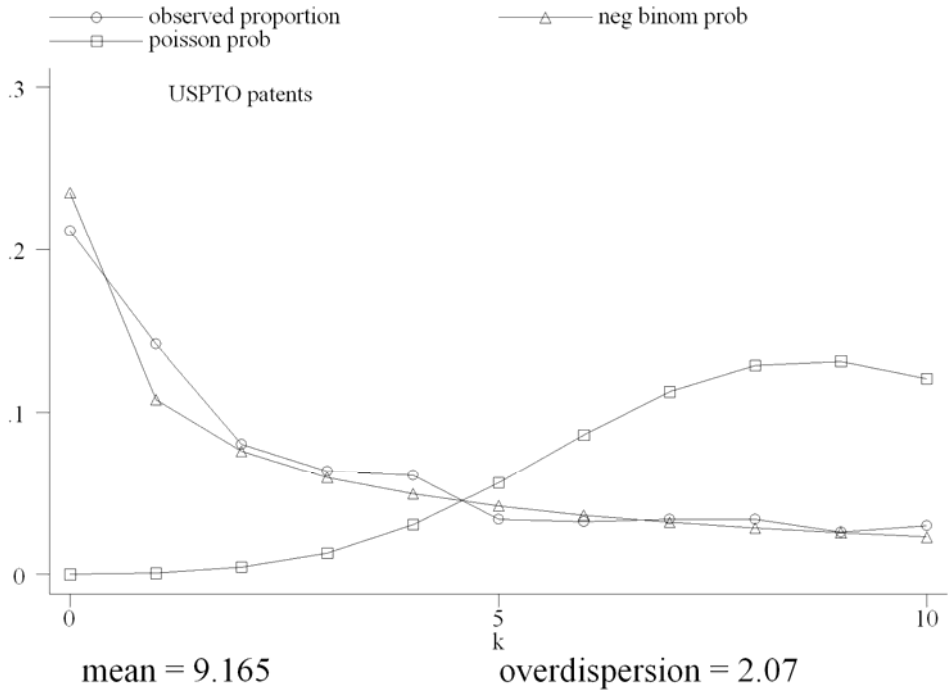
$$7)\ \log(L) = \sum_{i=1}^{n} \left\{ \ln\Gamma\left(\frac{1}{\alpha} + y_i\right) - \ln\Gamma(y_i + 1) - \ln\Gamma\left(\frac{1}{\alpha}\right) - \frac{1}{\alpha}\ln(1 + \alpha\mu_i) + y_i \ln\left(\frac{\alpha\mu_i}{\alpha\mu_i + 1}\right) \right\}$$

In this case, the value of the likelihood ratio test of the overdispersion parameter alpha, which reduces the negative binomial model to the Poisson one, is significantly different from zero. In the regressions, we get: $Chi^2(1)=600.26$ with $Prob>chi^2=0.000$ for EPO counts, $Chi^2(1)=883.40$ with $Prob>chi^2=0.000$ for USPTO counts, and $Chi^2(1)=1372.37.26$ with $Prob>chi^2=0.000$ for WIFO counts. Since these findings corroborate the hypothesis that the Poisson distribution is not appropriate, other specifications have to be used to obtain consistent estimates.

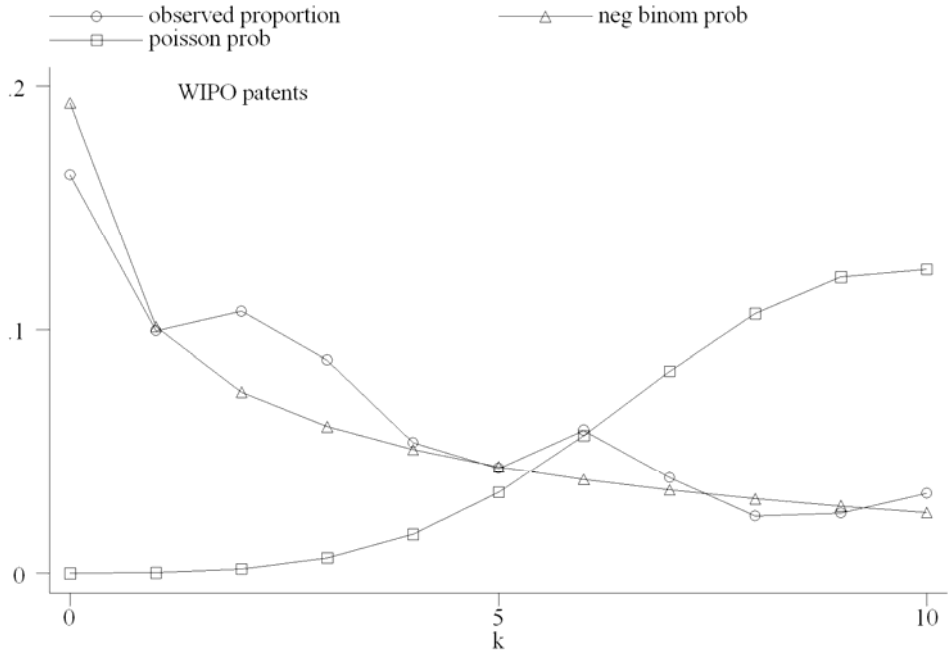
A simple graph comparing the actual distribution of our three patent counts with a Poisson distribution and a negative binomial distribution allows one to see in a clear-cut manner that the patent counts do not fit the Poisson model, but they *do* fit the negative binomial distribution very well (Figure 2). In fact, the negative binomial distribution accommodates for the most severe shortcomings of the Poisson regression: firstly, by addressing the unrealistic assumption of the Poisson regression, that there is no unobserved heterogeneity with the addition of an error term to its model equations; secondly, by adding what is called a "dispersion parameter" that accounts for differences between mean and variance.

Figure 2 – Actual, Poisson, and negative binomial distribution of patents counts: EPO, USPTO, WIPO





mean = 9.165 overdispersion = 2.07



mean = 10.26; overdispersion = 1.808

That the negative binomial model has to be preferred to the Poisson model in each group of estimates is also confirmed by the marked decrease of the value of the ratio of deviance to degrees of freedom (EPO: from 4.87 to 1.15; USPTO: from 6.85 to 0.91 and WIPO: from 9.35

to 0.98). However, for the sake of completeness, we also tested the possibility of using the GLM with a gamma distribution, where the variance is proportional to the square of the mean (μ^2). With this specification, the ratio of deviance to degrees of freedom is even lower than with the negative binomial one (EPO 0.92, USPTO 0.63, and WIPO 0.69).

5 Discussion

The summary of the estimates for the count models follows. However, before discussing the results from estimation of all the models introduced in the previous section – shown in Tables 4, 5, and 6, dealing respectively with EPO, USPTO, and WIPO patents – it is worth highlighting some considerations about the evidence arising from the correlation matrix in the Appendix (Table A.1).

Firstly, none of the dependent variables used for the various models and specifications is highly correlated with any of the independent variables. Secondly, as expected, the correlations among current, lagged, and squared values of R&D expenditures are high. Thirdly, correlations among current and lagged values of capital expenditures are lower, whereas that between current and squared values of the same variable are high. Fourthly, correlations between employment size and the various measures of R&D are much higher than those between employment size and the various measures of capital expenditures. Accordingly, whereas R&D expenditures seem to grow almost monotonically along with company size, the dynamics of capital expenditures seem to reflect a company's preference for one or another innovation strategy; with lower correlations likely denoting preference for a less market-oriented one. Fifthly, and most importantly, the correlations between R&D and capital expenditures are relatively high, in particular with the 2-year lagged capital expenditures variable (ranging between 0.70 and 0.73). This suggests that biotechnology companies invest in physical capital in one period to perform R&D in the subsequent ones, providing indirect support to the hypothesis that capital expenditure is somewhat specific with respect to the features of in-house R&D activities.

In Tables 4, 5, and 6 we also present an estimate of an OLS specification of $\log(n_{it}) = X_{it}b + e_{it}$ where $\log(n_{it})$ is set to zero and a dummy variable used when $n_{it} = 0$. The results from this estimate are presented in column I of each table, but they are not discussed in the remaining part of the Section. We have therefore limited our comments to the results from estimation of the other specifications. However, we already know that the values of the ratio of deviance to

degrees of freedom suggest that models (4) and (5), the negative binomial and gamma distributions, give regression outcomes which have to be preferred to those arising from models (2) and (3), namely the basic Poisson model and the Poisson model with standard errors adjusted for the estimated dispersion parameter.

Table 4 - Parameter estimates for the various models: EPO patents

EPO	I OLS	II Poisson	III Poisson s.e. adjusted	IV Neg. binomial	V Gamma
ln(R&D)	0.450*	0.107	0.107	-0.222	-0.163
	(1.92)	(0.56)	(0.21)	(0.45)	(0.24)
$\ln(R\&D)_{t-1}$	0.250	0.309*	0.309	0.282	0.319
	(1.27)	(1.96)	(0.73)	(0.64)	(0.57)
$\ln(R\&D)_{t-2}$	0.242*	0.828***	0.828**	0.771**	0.625*
	(1.68)	(6.31)	(2.35)	(2.47)	(1.67)
$\ln(R\&D)^2$	-0.080***	-0.059***	-0.059	-0.031	-0.018
	(3.38)	(3.21)	(1.20)	(0.65)	(0.28)
ln(CapExp)	0.066	0.555***	0.555*	0.620**	1.070***
	(0.57)	(4.80)	(1.79)	(2.51)	(3.35)
$\ln(CapExp)_{t-1}$	-0.006	-0.039	-0.039	-0.026	0.036
	(0.12)	(1.00)	(0.37)	(0.25)	(0.27)
$\ln(CapExp)_{t-2}$	-0.071	-0.244***	-0.244*	-0.298**	-0.340**
	(1.24)	(4.45)	(1.66)	(2.23)	(2.19)
$\ln(CapExp)^2$	-0.005	-0.088***	-0.088	-0.088*	-0.173***
	(0.22)	(4.35)	(1.62)	(1.91)	(2.88)
ln(Employees)	0.168**	0.407***	0.407***	0.468***	0.442***
	(2.76)	(8.33)	(3.11)	(3.43)	(2.70)
$z_{i,t}$ (time_trend)	-0.078*	-0.151***	-0.151*	-0.508***	-0.797***
	(1.74)	(4.52)	(1.69)	(5.10)	(5.52)
$a_{i,t}$ (dummy_eu)	1.171***	2.861***	2.861***	2.941***	3.399***
	(8.53)	(27.43)	(10.23)	(11.47)	(9.46)
dummy(y_i=0)	-0.838***				
	(7.81)				
Constant	-2.384***	-6.295***	-6.295***	-4.057***	-3.353**
	(4.12)	(14.96)	(5.58)	(3.97)	(2.54)
Observations	235	235	235	235	235
Test-chi^2	-	1086.521	-	-	-
Prob>chi^2(223)		0.0000			
R2-adj	0.56	-	-	-	-
Pseudo R^2		0.488	-	0.137	-
Deviance/df	-	4.87	4.87	1.15	0.92
Pearson/df	-	7.18	7.18	1.28	2.88
Log-likelihood	-	-755.48	-755.48	-455.36	-355.78
LR chi^2(11)	-	1441.33	-	145.07	-
Prob>chi^2	-	0.0000	-	0.0000	-

Absolute value of t statistics in parentheses. The superscripts mean: *significant at 10%; **significant at 5%; ***significant at 1%

Columns II in Tables 4, 5, and 6 show the estimates of the basic Poisson model. Results show some differences in the elasticity of the three patent counts to both the direct research effort put forward by each company in terms of in-house R&D and embodied technological change.

Coefficients of current and lagged R&D expenditures are in effect always significant for USPTO patents, whereas the current R&D component of the overall R&D elasticity of patents has a positive and significant coefficient for both USPTO and WIPO patents but not for EPO. The coefficient of the squared R&D is always negative. Current and lagged investments in new machinery and capital equipment (the *CapExp* variable) exert a weaker impact on firm patenting: the coefficient of the current value is positive and significant for USPTO and WIPO patents only, whereas the lagged values are never positive and significant. Decreasing returns of scale are confirmed for all measures by a negative and significant coefficient of the squared term.

Columns III in each table present estimations of the GLM Poisson model. For EPO patents, only R&D and capital expenditures lagged by two periods give a positive and statistically significant coefficient, along with company size and the dummy for EU companies. For both USPTO and WIPO patents also, current R&D and current capital expenditures are positive and significant, whereas the same finding for the basic Poisson model is found in relation to the squared term of both variables.

Columns IV and V present the estimates of the negative binomial and the gamma models, which have been shown in the previous section (cf. also figure 2 above) to be our preferred specifications. Accordingly, results with these models are given in more detail and are taken as a starting point for the discussion of the policy implications, which may be drawn from the analysis of the effects of R&D and capital expenditures on the patenting activities of biotechnology firms.

In general, for both R&D and capital expenditure variables, we find higher estimates when we use USPTO patents as a dependent variable. More specifically, we find that:

- the current R&D variable is never significant;
- the R&D variable lagged by 1 period is positive and significant (at a 5% confidence level) only in relation to USPTO patents, and for both models;
- the R&D variable lagged by 2 periods is significant for both EPO and USPTO with the negative binomial model (again at a 5% confidence level), whereas only for EPO patents and at a 10% confidence level with the gamma model;
- however, this variable gets the most significant (1% confidence level) coefficients with both models in the case of WIPO patents.

- the squared value of R&D expenditures is highly significant, but negative, in the case of USPTO patents, confirming only in part findings from estimation of the basic Poisson specification. Apparently, when patent applications with USPTO are used, there emerges some indication of decreasing returns to scale in R&D: as R&D expenditures increase, the number of patent applications increases at first, but then turns negative beyond a certain threshold.

- for both models, and in relation to patent applications with both EPO and USPTO, the coefficients of the current capital expenditures variable are positive and significant. However, this is less so (that is only at a 5% confidence level) in the case of the negative binomial model for EPO patents and in the gamma model for USPTO ones;

- coefficients of the 1-period lagged capital expenditures variable are never significant, irrespective of the source of patent data used;

- coefficients of the 2-period lagged capital expenditures variable are either non-significant (USPTO and WIPO patents) or negative and significant (EPO patents), which suggests a rapid exhaustion of the role played by physical assets as an indirect source of new knowledge output;

- the squared values of the capital expenditures variable are negative and significant for both EPO and USPTO data with the negative binomial model, whereas they are not significant for WIPO. Underlying a quadratic relationship between adoption of embodied technological change and creation of new patentable knowledge. This finding is consistent with the hypothesis of decreasing returns to scale in capital expenditures;

- in relation to WIPO patents, coefficients of the capital expenditures variables are never significant, with the only exception and just at a 10% confidence level, of the case in which it is lagged by two periods with the negative binomial model. Along with the high estimates found when we consider a 2-period lagged R&D, this finding may indicate that, although they are more likely to produce a major technological breakthrough, 'high' value patents are the result of long-term R&D programmes, and entail new knowledge which needs subsequent refinement before being turned into new products or processes.

As far as the control variables are concerned, we find that the number of patent applications always increases with company employment size, and that European firms tend to patent more with the EPO. The coefficient of the dummy variable for European companies is positive, and also (slightly) significant in relation to WIPO patents, but never significant in relation to USPTO patents.

Table 5 – Parameter estimates for the various models: USPTO patents

USPTO	I OLS	II Poisson	III Poisson s.e. adjusted	IV Neg. binomial	V Gamma
ln(R&D)	-0.317	0.716***	0.716**	0.355	0.275
	(1.10)	(5.56)	(2.07)	(1.00)	(0.71)
$\ln(R\&D)_{t-1}$	0.030	0.390***	0.390	0.602**	0.745**
	(0.13)	(3.59)	(1.34)	(2.08)	(2.29)
$\ln(R\&D)_{t-2}$	0.426**	0.653***	0.653***	0.430**	0.320
	(2.45)	(8.73)	(3.24)	(2.11)	(1.49)
$\ln(R\&D)^2$	0.036	-0.116***	-0.116***	-0.072**	-0.065*
	(1.25)	(11.11)	(4.13)	(2.14)	(1.77)
ln(CapExp)	0.190	0.302***	0.302**	0.404***	0.365**
	(1.41)	(6.32)	(2.35)	(2.62)	(2.24)
$\ln(CapExp)_{t-1}$	-0.049	-0.003	-0.003	-0.050	-0.074
	(0.91)	(0.19)	(0.07)	(0.83)	(1.18)
$\ln(CapExp)_{t-2}$	-0.030	-0.032	-0.032	-0.032	-0.015
	(0.44)	(1.16)	(0.43)	(0.41)	(0.18)
$\ln(CapExp)^2$	-0.026	-0.045***	-0.045**	-0.052**	-0.042
	(1.13)	(6.07)	(2.26)	(2.02)	(1.57)
ln(Employees)	0.297***	0.217***	0.217***	0.168**	0.131
	(4.01)	(7.96)	(2.96)	(2.10)	(1.49)
$z_{i,t}$ (time_trend)	-0.084	-0.045**	-0.045	-0.090	-0.113*
	(1.64)	(2.19)	(0.81)	(1.57)	(1.80)
$a_{i,t}$ (dummy_eu)	-0.057	0.068	0.068	0.121	0.161
	(0.39)	(1.18)	(0.44)	(0.74)	(0.88)
dummy(y_i=0)	-1.404***				
	(7.66)				
Constant	-0.811	-4.423***	-4.423***	-3.252***	-2.820***
	(1.14)	(13.90)	(5.17)	(4.14)	(3.65)
Observations	241	241	241	241	241
Test-chi^2	-	1568.179	-	-	-
Prob>chi^2(229)		0.0000			
R^2-adj	0.59	-	-	-	-
Pseudo R^2		0.503	-	0.11	-
Deviance/df	-	6.85	6.85	0.91	0.63
Pearson/df	-	7.24	7.24	0.73	0.92
Log-likelihood	-	-1191.37	-1191.37	-756.94	-735.73
LR chi^2(11)	-	2409.59	-	181.01	-
Prob>chi^2	-	0.0000	-	0.0000	-

Absolute value of t statistics in parentheses. The superscripts mean: *significant at 10%; **significant at 5%; ***significant at 1%

Whereas it seems obvious that the number of patent applications is strongly related to company size, the preference of European firms to patent with EPO rather than with USPTO or through the WIPO procedure reflects, at least in part, the structural features of biotechnology in Europe as compared to the US. In fact, European biotechnology firms are younger and worse positioned in international markets than their American counterparts, and are seriously affected by a lack of financial resources to enhance their competitiveness and sustainability (Critical I, 2006). Structural weaknesses are therefore likely to limit their access

to the US technological market, making the USPTO a less viable patent institution than the EPO.

Table 6 – Parameter estimates for the various models: WIPO patents

WIPO	I OLS	II Poisson	III Poisson s.e. adjusted	IV Neg. binomial	V Gamma
ln(R&D)	-0.229	0.950***	0.950**	0.239	0.118
	(0.76)	(8.16)	(2.43)	(0.66)	(0.28)
$\ln(R\&D)_{t-1}$	-0.120	0.013	0.013	-0.009	-0.030
	(0.48)	(0.12)	(0.04)	(0.03)	(0.09)
$\ln(R\&D)_{t-2}$	0.479***	0.713***	0.713***	0.681***	0.723***
	(2.64)	(10.05)	(3.00)	(3.28)	(3.10)
$\ln(R\&D)^2$	0.046	-0.100***	-0.100***	-0.009	0.007
	(1.52)	(11.07)	(3.30)	(0.25)	(0.17)
ln(CapExp)	0.124	0.056	0.056	0.191	0.238
	(0.890)	(1.30)	(0.39)	(1.29)	(1.41)
$\ln(CapExp)_{t-1}$	-0.046	-0.003	-0.003	-0.052	-0.062
	(0.83)	(0.18)	(0.05)	(0.83)	(0.87)
$\ln(CapExp)_{t-2}$	-0.148**	-0.172***	-0.172**	-0.144*	-0.151
	(2.06)	(6.65)	(1.98)	(1.72)	(1.56)
$\ln(CapExp)^2$	-0.025	-0.018***	-0.018	-0.036	-0.046
	(1.04)	(2.72)	(0.81)	(1.32)	(1.40)
ln(Employees)	0.347***	0.369***	0.369***	0.232***	0.209**
	(4.34)	(14.45)	(4.31)	(2.61)	(2.02)
$z_{i,t}$ (time_trend)	-0.028	-0.093***	-0.093	-0.103	-0.115
	(0.52)	(4.78)	(1.43)	(1.63)	(1.56)
$a_{i,t}$ (dummy_eu)	0.132	0.495***	0.495***	0.407**	0.399*
	(0.85)	(10.02)	(2.99)	(2.33)	(1.96)
dummy(y_i=0)	-1.685***				
	(7.88)				
Constant	-1.047	-4.438***	-4.438***	-2.055***	-1.721**
	(1.43)	(15.90)	(4.74)	(2.70)	(2.05)
Observations	237	237	237	237	237
Test-chi^2	-	2104.69	-	-	-
Prob>chi^2(225)		0.0000			
R2-adj	0.384	-	-	-	-
Pseudo R^2		0.455	-	0.08	-
Deviance/df	-	9.35	9.35	0.98	0.69
Pearson/df	-	11.25	11.25	0.96	1.13
Log-likelihood	-	-1477.84	-1477.84	-795.39	-780.01
LR chi^2(11)	-	2466.77	-	144.80	-
Prob>chi^2	-	0.0000	-	0.0000	-

Absolute value of t statistics in parentheses. The superscripts mean: *significant at 10%; **significant at 5%; ***significant at 1%

To summarise, at least with EPO and USPTO patent applications, the finding with the *CapExp* variable is consistent with our hypothesis that the adoption of improved machinery and capital equipment may play a crucial role in the development of new patentable items, not necessarily

less important than that played by R&D expenditures.[20] This implies R&D acts more in a complementary fashion to capital expenditures, rather than replacing it, for science-based industries pursuing an innovation strategy targeting new product development. Washing, decontamination, sterilisation, pure steam and distillation devices may prove fundamental to improve the quality of R&D activities and maximise production uptime. It could also be argued that both the company's ability to discover and invent, as well as its investments in physical assets with embodied technological change, are crucial for obtaining patentable inventions. This is consistent with the findings by Hall and Ziedonis[21] (2001) for the semiconductor industry, and supports the hypothesis that capital investment may exert an important effect on the propensity to patent in science-based industries, possibly even larger than that of R&D spending itself.

6 Conclusions and policy implications

This paper has analysed the impact of R&D investment and capital expenditures on the knowledge output of a sample of companies active in the biotechnology field. Findings point out that, for both EPO and USPTO patent applications, current capital expenditures represent the major driver of new knowledge creation. With USPTO patents, a major determinant of new knowledge creation is also R&D expenditures lagged by 1 and 2 periods. For WIPO patents, only R&D expenditures lagged by 2 periods is positive and significant among our core independent variables of interest. The squared values of the capital expenditures variable are negative and significant with both the EPO and the USPTO data, which suggests a non-linear relationship between adoption of embodied technological change and creation of new patentable knowledge. The coefficients of the control variables suggest that European companies are more likely to apply for patent protection with the EPO, and the number of patent applications always increases with company size. The latter finding is straightforward. The former, along with the results obtained with the variables of interest, leads to some policy recommendations for Europe.

These results clearly demonstrate that R&D *and* capital expenditures are complementary forces and determinants in the overall innovation process.

[20] For the population of Italian DBFs, Santarelli and Lotti (2008) found a strong positive and statistically significant relationship between patents with EPO and profitability.
[21] Even though they use a stock measure such as *capital intensity*, i.e. the capital-labour ratio.

Combined with the results of studies dealing with both the beginning of modern biotechnology in the US (Santarelli, 1995) and some recent trends in European biotechnology (Critical I, 2006; European Commission, 2009a), showing that biopharmaceutical firms are affected by a large funding gap when involved in product development, the findings found in this paper suggest that innovation policies and policies aimed at promoting the emergence of science-based industries should pay more attention to supporting the companies' investment in new machinery and capital equipment. This is particularly so in Europe, where biotechnology firms are facing the negative consequences of a fragmented equity market, ultimately resulting in a substantial equity gap which further limits their ability to undertake the investment necessary to bring products to market (Fazeli, 2005).

Moreover, the greater propensity of European biotechnology companies to patent with the EPO, as found in this study, is a further argument in support of a rapid completion of a European patent system to reduce incongruities of heterogeneous national enforcement practices and litigation costs. High fragmentation of the European patent system, the lack of a unitary title, the absence of a unified patent litigation system and the presence of nationally granted patents have so far hampered enforcement of EPO patents (van Pottelsberghe de la Potterie and Guellec, 2007; de Rassenfosse and van Pottelsberghe de la Potterie, 2009; van Pottelsberghe de la Potterie, 2010). Enhancing legal measures in relation to their patenting activities would strengthen the competitiveness of European high-tech firms, as would an integrated judicial system, entailing common rules. A common appeal court[22] might also serve this purpose. This is also consistent with the recommendation from the European Commission to the Council for the adoption of an agreement creating a Unified Patent Litigation System (European Commission, 2009b).

To summarise, at least in relation to the standard patenting activity of biotechnology firms, the findings in this paper allow us to change the question raised in the title into a straightforward statement: *The better you spend (on R&D and dedicated physical assets), the more (patents) you get*. Future research should explore the simultaneous impact of R&D, capital expenditure, and patenting in productivity growth and profitability performance.

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[22] Possibly trying to avoid the drawbacks consequent upon the creation of CAFC in the United States. See Section 3 above.

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Annex

Table A.1 – Correlation matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	log(EPO)	1.0000								
(2)	log(USPTO)	0.2008	1.0000							
(3)	log(WIPO)	0.2918	0.6915	1.0000						
(4)	EPO	0.7750	0.2138	0.2995	1.0000					
(5)	USPTO	0.1610	0.8174	0.6080	0.2093	1.0000				
(6)	WIPO	0.2926	0.6178	0.8109	0.3871	0.7414	1.0000			
(7)	log(R&D)	-0.0598	0.6766	0.6102	0.0127	0.6093	0.5410	1.0000		
(8)	$\log(R\&D)_{t-1}$	-0.0434	0.6947	0.6147	0.0247	0.6377	0.5532	0.9627	1.0000	
(9)	$\log(R\&D)_{t-2}$	-0.0264	0.7008	0.6244	0.0358	0.6512	0.5644	0.9297	0.9627	1.0000
(10)	$[\log(R\&D)]^2$	-0.0638	0.6590	0.5979	0.0013	0.6301	0.5635	0.9771	0.9455	0.9100
(11)	log(CapExp)	0.0749	0.3107	0.2216	0.0464	0.2397	0.1702	0.3822	0.3593	0.3337
(12)	$\log(CapExp)_{t-1}$	0.0907	0.4311	0.3636	0.0751	0.4185	0.3686	0.5850	0.5805	0.5566
(13)	$\log(CapExp)_{t-2}$	0.0577	0.5386	0.4640	0.1012	0.5623	0.4923	0.7080	0.7308	0.7281
(14)	$[\log(CapExp)]^2$	0.0372	0.2940	0.2143	0.0173	0.2395	0.1793	0.4111	0.3872	0.3670
(15)	log(Employees)	0.1378	0.5113	0.4537	0.1816	0.5299	0.5262	0.6179	0.6118	0.5926
(16)	time_trend	-0.1157	-0.0213	0.0199	-0.0069	0.0106	0.0157	0.0328	0.0702	0.0443
(17)	dummy_eu	0.5014	-0.4166	-0.3000	0.3461	-0.3150	-0.1873	-0.6012	-0.6002	-0.5944

		(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(10)	$[\log(R\&D)]^2$	1.0000							
(11)	log(CapExp)	0.3884	1.0000						
(12)	$\log(CapExp)_{t-1}$	0.6027	0.5640	1.0000					
(13)	$\log(CapExp)_{t-2}$	0.7347	0.3533	0.6592	1.0000				
(14)	$[\log(CapExp)]^2$	0.4350	0.9487	0.5680	0.3628	1.0000			
(15)	log(Employees)	0.6465	0.2948	0.6074	0.7886	0.2817	1.0000		
(16)	time_trend	0.0338	-0.0848	-0.0420	-0.0744	-0.1253	0.0420	1.0000	
(17)	dummy_eu	-0.5431	-0.2072	-0.2603	-0.3344	-0.2181	-0.2364	0.0291	1.0000

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Abstract

This paper provides evidence on the mechanisms influencing the patent output of a sample of biotechnology firms from the input of *indirect* knowledge acquired from capital expenditure and *direct* knowledge from in-house R&D. Statistical models of counts are used to analyse the relationship between patent applications and R&D and capital expenditure. It focuses on biotechnology in the period 2002-2007 and is based on a unique data set drawn from various sources including the *EU Industrial R&D Investment Scoreboard*, the European Patent Office (EPO), the US Patent and Trademark Office (USPTO), and the World Intellectual Property Organisation (WIPO/PCT).

The statistical models employed in the paper are Poisson distribution generalisations with the actual distribution of patent counts fitting the negative binomial distribution and gamma distribution very well.

Findings support the idea that capital expenditure – taken as equivalent to technological change embodied in new machinery and capital equipment - may also play a crucial role in the development of new patentable items from scientific companies. For EPO patents, this role appears even more important than that played by R&D expenditure.

The overall picture emerging from our analysis of the determinants of patenting in biotechnology is that the innovation process involves a well balanced combination of inputs from both R&D and new machinery and capital equipment.

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