The More You Spend, the More You Get? The Effect of R&D and Capital Expenditures on Biotechnology Patents*

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Abstract

This paper uses statistical models of counts to analyze the relationship between patents on the one side and R&D and capital expenditures on the other. It focuses on the biotechnology industry over the 2002-2007 period and is based on a unique data set drawn from various sources including the *EU Industrial R&D Investment Scoreboard*, the U.S. Patent and Trademark Office (USPTO), the European Patent Office (EPO), and the World Intellectual Property Organization (WIPO).

The statistical models employed in the paper are applications and generalizations of the Poisson distribution and show that the actual distribution of patent counts fits very well the negative binomial distribution.

Our findings support the idea that expenditures in improved machinery and capital equipment may play a crucial role in the development of new patentable items, a role not necessarily less important than that played by R&D expenditures. This implies complementarity rather than substitutability between R&D and capital expenditures, also in a science-based industry such as biotechnology. The overall picture emerging from our analysis of the determinants of patenting in the biotechnology industry is therefore not fully consistent with some pessimistic views on the innovativeness of this industry. What actually emerges is rather that successful innovative activities in biotechnology should imply a well balanced combination of both R&D and embodied technological change as main inputs to the innovation process.

JEL Classification: L25; L65; O34;

Keywords: Patents; R&D; Capital expenditures; Poisson models; Biotechnology industry.

Version: 14 February 2010

* Enrico Santarelli acknowledges financial support from MIUR (PRIN 2006, "Innovation, Entrepreneurship, and Competitiveness of Italian Firms in the High-Tech Industries"; protocol #2006132439). We thank Timon Gaertner for assistance in data collection. The views expressed by Roberta Piergiovanni do not necessarily reflect those of Istat.

1. Introduction

Biotechnology is highly composite in nature, including the sub-fields of agricultural (in turn subdivided into plant and animal cell technologies), medical, microbial and marine biotechnology. It is multidisciplinary from both a scientific and a technological perspective. From a scientific perspective, it encompasses molecular biology, biochemistry, genetics, genomics, bioinformatics and environmental sciences. From a technological perspective, it encompasses recombinant DNA technology, gene transfer, embryo manipulation and transfer, monoclonal antibody production, and bioprocess engineering.

Biotechnology is also highly versatile, since it can be used in a number of industrial applications and for 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, and more. Thus, if one follows an 'object approach' (Archibugi, Evangelista and Simonetti, 1994) biotechnology is part of a model of technological change in which product innovation, often of an incremental nature, is driven by process innovation.

Finally, biotechnology 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 which make it possible to produce bread, alcohol and cheese. What is new and has given rise to the myth of a 'biotech revolution' are the tools that scientists nowadays use to modify organisms, enabling them to alter an organisms' DNA with much greater precision than in the past. Accordingly, contemporary biotechnology is not a new technological paradigm in the sense of Dosi (1982). Rather, it is 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 potentially many new applications of biotechnology itself (Wonglimpiyarat, 2008; Santarelli and Lotti, 2008).

However, at least in the medicinal biotechnology industry the relationship between R&D expenditures and patenting is a typical case to which the so-called "productivity paradox" argument applies (David, 1990). As argued by Nightingale and Martin (2004) and thoroughly demonstrated by Hopkins et al. (2007), no truly convincing empirical evidence has been so far provided supporting the existence of a biotech revolution able to

bring about economic development as a result of improvements, among others, in the drug discovery process and in healthcare. Following the path of other 'general purpose engines', such as the electric dynamo at the edge of the Second Industrial Revolution (David, 1990), it is for example likely that the expansion of medicinal biotechnology into a number of areas of application will require a time much longer than originally expected and the achievement of complementary technological and organizational changes (David, 1990; von Tunzelmann, 1993). Consequently, many over-optimistic expectations have to be rethought and translation of the substantial changes in the biological sciences and the organization of R&D already occurred within this industry be given time for resulting into significantly improved or entirely new commercial products (Nightingale and Martin, 2004). Among the paradox of this missing revolution is that in spite of a significant increase in R&D expenditures and an increasing propensity to patent in industry, over the last decade medicinal biotechnology has experienced a substantial decline in R&D productivity.

From a theoretical viewpoint, this finding would raise doubts about the appropriateness of the usual assumption of constant returns to scale in R&D (Pakes and Griliches, 1980; Hausman et al, 1984; Griliches, 1990; Crepon and Duguet, 1997; Cincera, 1997; Blundell et al., 2002; Denicolò, 2007)) and has therefore to be subjected to further investigation. From an empirical viewpoint, this finding would instead raise the spectre of anticipated technological exhaustion and of a vicious circle in which lower innovative output would reduce both the private return to R&D and the equilibrium level of R&D investment (Lanjouw and Schankerman, 2004). Thus, should the decline in R&D productivity be confirmed by the data the standard statement *the more you spend (in R&D), the more you get (in terms of patent output)* would not hold any more for this important science-based industry.

However, it is not clear whether the skeptical considerations which apply to medicinal biotechnology can be generalized to the whole field. In fact, there is evidence that the picture is much less obscure for some emerging areas of industrial biotechnology, such as those of cellulase-related enzymes and enzymes for bio-based plastics production (US International Trade Commission, 2008).

In the light of the above considerations, this paper is aimed at exploring the impact exerted on the production of new (patented) knowledge by R&D spending (as a proxy of the *direct* knowledge inputs in the innovation process) and capital expenditures (as a proxy of the most crucial *indirect* knowledge input in the innovation process, namely technological change embodied in new machinery and capital equipment) for the whole field of biotechnology. With firm size used as control variable. The analysis is carried out in relation to the innovative performance of firms included in subsequent releases of the *EU Industrial R&D Investment Scoreboard*, over the period between 2002 and 2007.

It is well known that R&D does not represent the sole input through which firms can produce some innovative outcomes. However, whereas the study of the impact of current and past R&D expenditures has become quite a standard exercise in the innovation literature, less attention has been traditionally paid to that of capital expenditures (for a recent contribution dealing with newborn firms, see Pellegrino., 2009). The latter has in fact been mostly considered in studies dealing with low- and medium-technology industries characterized by the widespread presence of small firms for which, consistent with Pavitt's (1984) definition of supplier-dominated firms, it is the main and sometimes only determinant of innovation (Santarelli and Sterlacchini, 1990; Santamaría et al., 2009). Thus, to our knowledge this is among the few attempts to look at the combined effect of R&D and capital expenditures on patenting in a science-based industry in Pavitt's (1984) terms.[1] According to Pavitt (1984), for science-based firms in-house R&D is the main source of technological change, with a crucial role also played by interaction with universities and research labs also important. The outcome of inventive activities performed by these firms is characterized by high appropriability and firms recur systematically to patent protection.

Even though at the center of a well-known controversy between Dale Jorgenson and Robert Solow already in the 1960s (for a survey, cf. Hercowitz, 1998), the role of technological change embodied in the new capital equipment as a major determinant of productivity growth at the firm level has been analyzed in depth only since the study by Terleckyj (1974), who assumed that external or "used" R&D is mainly embodied in

[1] One important exception for a science-based industry (semiconductors) is Hall and Ziedonis (2001). For a recent contribution dealing with newborn firms, see Pellegrino et al., 2009).

intermediate and capital goods. Accordingly, R&D activities undertaken by firms in different industries and embodied in the capital goods that they produce diffuse to the rest of the productive system according to the direct purchases of capital and intermediate inputs. With this procedure, the extent of external or "embodied" R&D has been shown to contribute effectively to explain the rates of productivity growth of US manufacturing industries (Santarelli and Sterlacchini, 1994). In the overall innovation process characterizing a science-based industry such as biotechnology, it is likely that investment in new capital equipment or to upgrade the existing one become more crucial when the knowledge created by means of R&D expenditures is about to be used for new product development. From such a perspective, capital expenditures might be complementary to R&D expenditures. In fact, if one follows Greenwood and Yorukoglu (1997, p. 49) one may argue that at a certain point of the evolution of the biotechnology industry an "era of rapid investment-specific technological progress" has come, making learning-by-doing and embodied technological change crucial for turning the new knowledge already created by means of R&D into viable product innovations.

The paper is organized as follows. Section 2 presents the database, which has been developed by combining data from various sources to arrive at a new and unique dataset. Section 3 introduces variables and models, besides discussing some estimation problems typically arising in analysis of events involving non-negative integer counts has is the case with patents. Section 4 presents and discusses the estimation results. Finally, Section 5 concludes, summarizing the main results and offering some hints for firm strategy and innovation policy.

2. Data and summary statistics

Created in response to the Commission's Research Investment Action Plan 19, aimed at reducing the gap between the EU's R&D investment and that of other developed economies, the *EU Industrial R&D Investment Scoreboard* (the *Scoreboard*) provides information on the 1000 EU and 1000 non-EU listed and non-listed companies investing the largest sums in R&D in the previous reporting year. It is drawn from a database containing information extracted from the audited annual reports and accounts of companies.

The R&D investment considered for the *Scoreboard* is the cash investment directly funded by the companies, with the R&D performed under contract for customers such as governments or other companies (either independent or associated) excluded. 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. This drawback makes therefore inappropriate the use of these data for cross-country comparisons but does not undermine its usefulness for firm-level analysis.

The *Scoreboard* provides also data on capital expenditures, corresponding to expenditure used by a company to acquire or upgrade physical assets such as equipment, property, industrial buildings. In accounts capital expenditure is added to an asset account (i.e. capitalized), thus increasing the asset's base. In company's accounts capital expenditures are disclosed as additions to tangible fixed assets.

Up to the last release, the *Scoreboard* does not collect patent information. For this reason, we performed a search for patent applications with the European Patent Office (EPO) and the U.S. Patents and Trademark Office (USPTO) and for those included in the *WIPO/PCT Patents Fulltext* database published under the auspices of the World Intellectual Property Organization (WIPO) since 1978 and covering 177 states participating in the Patent Cooperation Treaty.[2] In consideration of the fact that firms may and may not be included in subsequent releases of the *Scoreboard*, what we have here is an unbalanced panel with a minimum of 97 (in 2002) and a maximum of 123 (in 2007) firms in each of the 6 years.

In Table 1 some descriptive statistics about biotechnology-related patent applications by the biotechnology firms comprised in the *Scoreboard* during the 2002-2007 period are presented, as a preliminary exploration of our data. Noteworthy in the data is the fact that, as suggested by the low value of the standard deviation EPO patents are more homogeneously distributed across firms than the other two types of patents, with an average of just three per firm over the period.

[2] Applications with WIPO have substantially a pre-emptive nature. Thus, they identify a sort of pre-patenting area that is less representative of the "true" patenting activities performed at the firm level.

Since firms in our database are those investing the largest sums in biotech R&D, it has to be expected that a significant portion of them combine important manufacturing capabilities with (equally) important research capabilities. This suggests, consistent with Hall and Ziedonis (2001) that they might tend to rely on both capital equipment and patents to recoup investments in R&D. Accordingly, they should be characterized by a large number of patent applications and heavy investments in both R&D and capital equipment. In fact, Table 2 shows that in each year firms invest heavily in both R&D and capital equipment, with average expenditures on R&D growing almost monotonically over time (from 65.5 in 2002 to 73.5 in 2007 million €), and capital expenditures displaying a more erratic pattern (with a period-low in 2007).

Table 1 – Summary statistics for patents 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

Noteworthy in Table 3 is the fact that about 50 per cent of firms have more than 250 employees, with one third exceeding the threshold of 500 employees. Some of the about 13 percent of firms that are shown in Table 3 to have fewer than 50 employees are probably “fabless”, or pure research firms or firms that do not perform manufacturing

activities in the field of biotechnology. In effect, over the entire period firms which make no capital expenditures and employ less than 50 employees represents 48.7% of the total.[3]

Table 2 – Summary statistics for firm-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€.

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

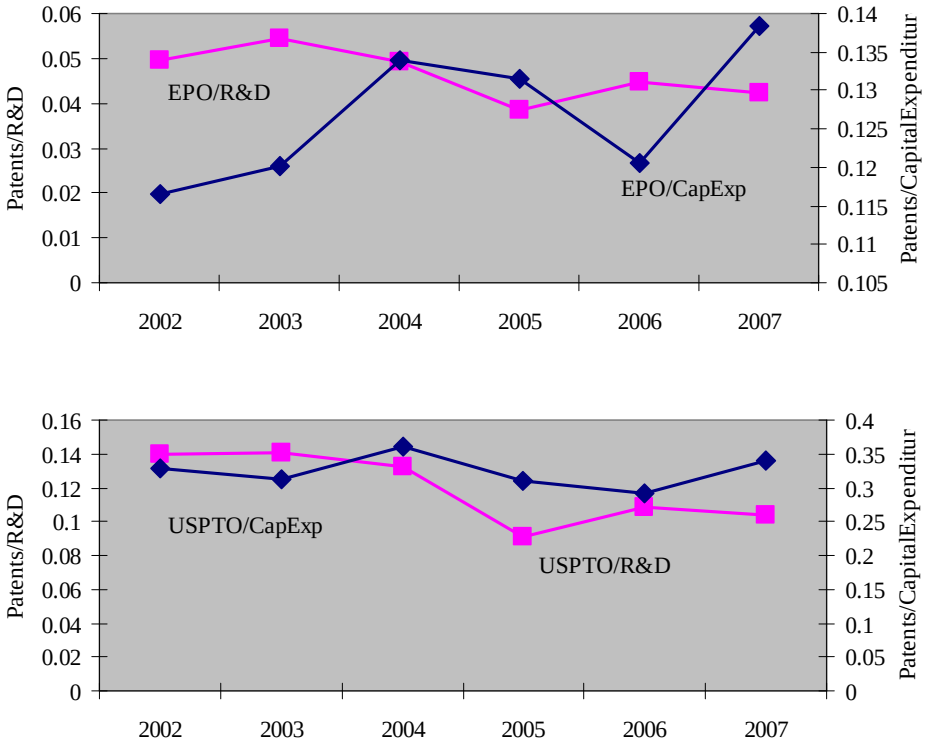
	1-49	50-249	250-499	500 and more	Total
2002	13	35	16	33	97
2003	12	37	21	33	103
2004	12	42	18	36	108
2005	11	43	15	41	110
2006	15	35	18	41	109
2007	15	48	18	42	123

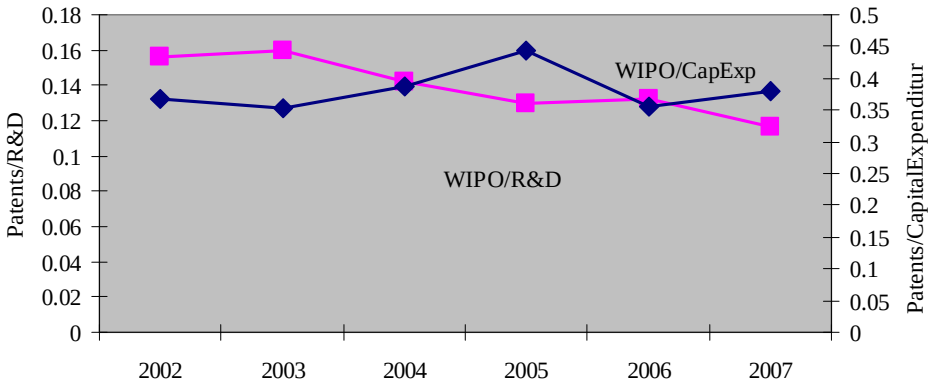
By keeping the three sources of patent data separate, in Figure 1 we show the patent/R&D and patent/capital expenditures ratio for all the biotech firms in the sample. The two ratios follow different trends: whereas the patent/R&D one turns out to be (slightly) decreasing over time for each type of patent,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

[3] And this explains the minimum values equal zero which have been found for capital expenditures between 2002 and 2006.

one, even though exhibiting a more erratic pattern, is clearly increasing. Does this mean that the productivity paradox discussed in Section 1 afflicts the biotechnology industry, with the consequence that in-house R&D is losing ground as main determinant of innovation? And that, accordingly, innovation is mainly dependent on embodied technical change acquired by means of investment in new machinery and capital equipment? Or this descriptive evidence simply reflects the fact that the industry is in the phase of transition from an "entrepreneurial technological regime" to a "routinized technological regime" (Malerba and Orsenigo, 1993; Audretsch, 1995), with the former dominated by newly established science-based firms, and the latter characterized by larger firms more focused on the production of new products based on the new knowledge that they have developed in the previous period by performing research and experimental development activities?

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





Since we simply perform patent counts, answering the above questions is quite uneasy. For example, analysis of the citations made by each patent to identify its antecedents might provide evidence consistent with the "transition" hypothesis should an increase in the number of self-citations over time be found. In fact, a growing proportion of citations made by the same assignee as the one owing the cited patent may reflect a higher appropriability by the organization that owns the cited patent and be clear sign that it is developing or has already developed a new innovative cluster upon which it exerts full control (Trajtenberg et al., 2002). One may therefore assume that a large number of patents building upon one or a few previous patent(s) owned by the same firm signal that such firm is refining and centering its innovation strategy around the development of a new specific innovative cluster. However, since our database does not contain information on patent citations exploration of this hypothesis is left to future research and at this stage we can only get indirect evidence consistent with the hypothesis.

3. Model specification

In order to detect whether R&D expenditures, embodied technological change, and firm size have affected the production of new inventive output in the biotechnology industry over the 2002-2007 period, we used various procedures besides the usual OLS one,[4] all of which based on a generalised linear model (GLM) which extends the

[4] It is worth recalling that with count variables the regression cannot be linear. 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.

traditional linear model to a wider range of data analysis problems using a function to link the expected response mean to a linear function of the explanatory variables. For the probability distribution of the dependent variable we assume 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 count of patents applied for by firm *i* in year *t*, ($\alpha_{i,t}$) are fixed effects for two firm types (European and non-European)[5], and ($z_{i,t}$) are time fixed effects captured by a time trend. The other independent variables are our firm-specific variables - that is in-house R&D[6] and its lagged (by 1, and 2 years) and squared values, capital expenditures[7] and its lagged (by 1, and 2 years) and squared values, employment size[8] - and a dummy variable $D(n_{i,t}=0)_{i,t}$ included when $n_{i,t}$= 0. Finally, an error term is included:

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

The distribution of patents applications with each of the three sources taken into account (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

[5] For the purposes of the *Scoreboard*, companies are allocated to the country of their registered office, that sometimes can be different from the operational or R&D headquarters. The main implication is that firm location is independent from 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. Only where these engineering costs have been disclosed separately, they have been excluded from the *Scoreboard*. Accordingly, an overstatement of some overseas R&D investment figures in comparison with the EU is possible.

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

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

[8] Defined as the total consolidated average employees or year-end employees if average not stated.

given year, statistical models for non-negative integers are the most appropriate analytical tools.

Thus, we try with different applications and generalizations of the Poisson distribution. In particular, the count of patents registered with EPO, USPTO and reported in the WIPO/PCT file by the biotechnology firms comprised in our sample is analyzed by estimating the following specification, in which the probability to observe $y_{i,t}$ 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 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:

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

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 assuming that that the transformed mean follows a linear model:

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

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

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

Increasing x_i by one unit multiplies the mean by a factor $\boldsymbol{e^{\beta}}$. Finally the model become:

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

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

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

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

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

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

As aptly shown by Crepon and Duguet (1997, p. 245), various weaknesses characterize the basic Poisson model. 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. Besides, the Poisson regression restricts the response variable to have mean equal to 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 (standard errors biased downward) of the estimates, with these inconsistent variance estimates invalidating any hypothesis testing. Thus, the Poisson regression model rarely fits in practice 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. Besides, the values of deviance and of the Pearson χ^2 dispersion indicate that there is overdispersion (larger more 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 that is necessary results in a loss of efficiency of the coefficients

In accordance with the results of the above tests, we run a generalized 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, we scale the standard error 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.

An alternative to scaling the standard errors would be to use a different distribution than the Poisson distribution. One which would allow for the variance to be greater than the mean. We therefore analyze the data with a negative binomial distribution (model IV in Tables 4-5) (Greenwood and Yule, 1920; Agresti, 2002), assuming that the dependent variable is overdispersed and does not have an excessive number of zeros. 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 patents 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 vector of regressors $\mathbf{x}_i$. Then the distribution of y_i conditional on $\mathbf{x}_i$ and τ_i is Poisson conditional mean and conditional variance $\mu_i \tau_i$:

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

Let g(τ_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 mean equal to 1 and 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 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:

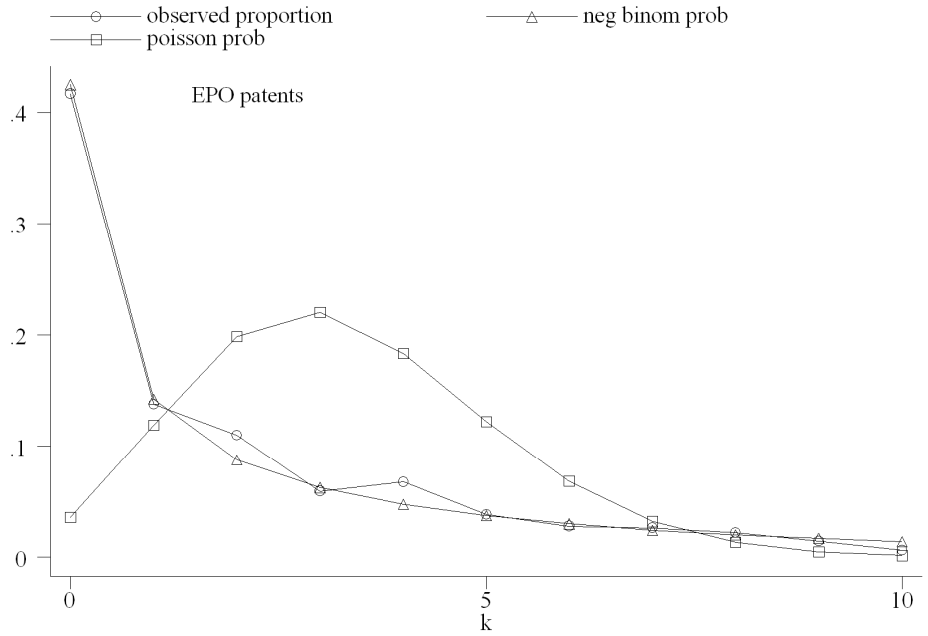
$$7)\ \log(L) = \sum_{i=1}^{n} \left\{ \ln\Gamma(\frac{1}{\alpha} + y_i) - \ln\Gamma(y_i + 1) - \ln\Gamma(\frac{1}{\alpha}) - \frac{1}{\alpha}\ln(1 + \alpha\mu_i) + y_i \ln(\frac{\alpha\mu_i}{\alpha\mu_i + 1}) \right\}$$

In this case the value of the overdispersion test statistic turns out to be significantly different from zero[9] and this finding corroborates the hypothesis that the Poisson distribution is not appropriate.

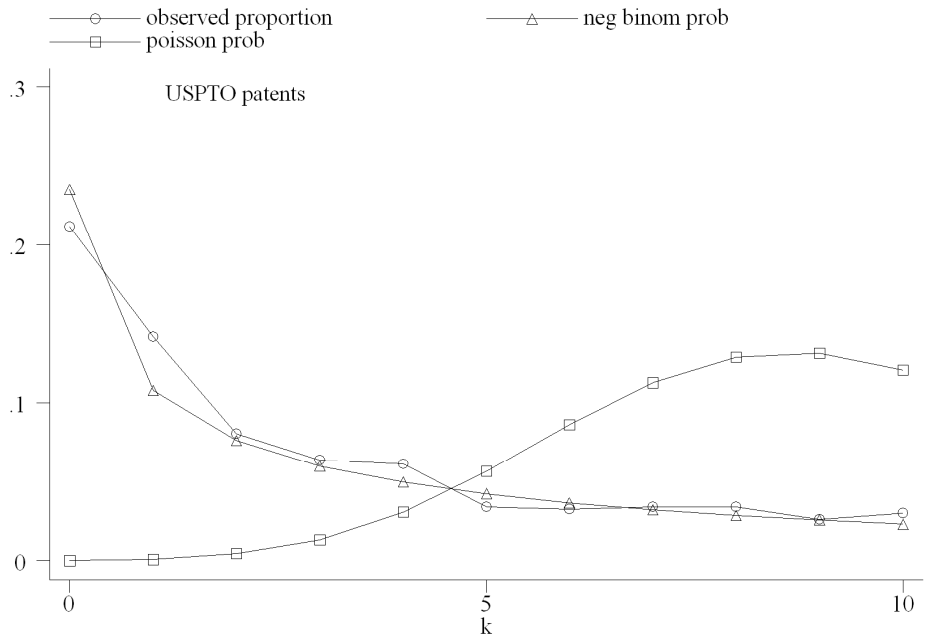
A simple graph comparing the actual distribution of our patent counts with a Poisson distribution and a negative binomial distribution allows one to see that the patent counts do not fit the Poisson model, but they *do* fit very well the negative binomial distribution (Figure 2).

[9] The likelihood ratio test of the overdispersion parameter alpha is significantly different from zero. In the regression for EPO counts we get: $Chi^2(1)=600.26$ with $Prob>chi^2=0.000$.

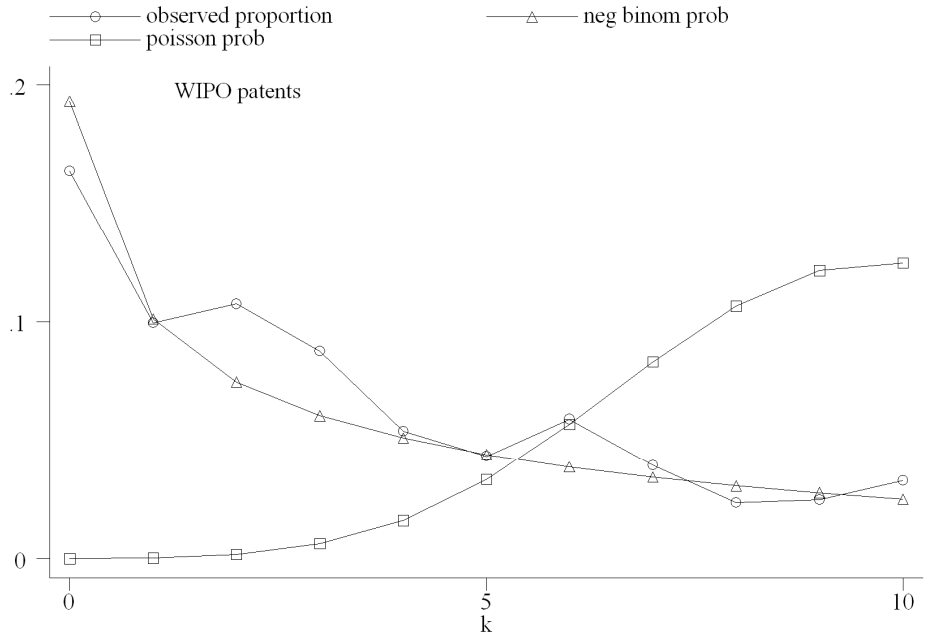
Figure 2 – Actual, Poisson, and negative binomial distribution of patents counts: EPO, USPTO, WIPO



mean = 3.332; overdispersion = 2.684



mean = 9.165 overdispersion = 2.07



mean = 10.26; overdispersion = 1.808

In fact, the negative binomial distribution accommodates for the shortcomings of the Poisson regression. It addresses the unrealistic assumption of the Poisson regression, that there is no unobserved heterogeneity, by adding an error term to its model equations. It also adds what is called a "dispersion parameter" that accounts for differences between mean and variance. The results of the negative binomial regression make it clear that this corrected version of the Poisson model is preferable, as the value for the ratio (deviance on the degrees of freedom) decreases markedly in each case (EPO: from 4.9 to 1.2; USPTO: from 6.8 to 0.9 and WIPO: from 9.4 to 1.0).

With the negative binomial model $RD_{t,i}^2$, $CapExp_{i,t}$, $CapExp_{i,t}^2$, $CapExp_{i,t-2}$ and $Emp_{i,t}$ are significant, whereas the other variables are not.

Finally, we used also a GLM with a gamma distribution where the variance is proportional to the square of the mean (μ^2) - model V in Tables 4-5 - for which the coefficients and the standard errors are similar to those obtained from the negative binomial model, although with a lower deviance on the degrees of freedom (EPO 0.92, USPTO 0.6, and WIPO 0.7).

4. Empirical results

The results are presented in Tables 4, 5, and 6 dealing respectively with EPO, USPTO, and WIPO patents. We also replicate the same estimate of an OLS 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 OLS estimates are presented in column I of each table, but they are not discussed in the remaining of the Section.

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)
$\ln(CapExp)_{t-1}$	-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%

The shortcomings of the various specifications discussed in previous section notwithstanding, let us now summarize our estimates of the elasticity of patenting with respect to R&D and capital expenditures for the count models. In fact¸ the values of the ratio of the deviance on the degrees of freedom clearly suggest that model (4), the negative binomial regression, is the preferred regression outcomes.

Columns II in Tables 4, 5, and 6 present 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 firm in terms of in-house R&D and embodied technological change. Current and lagged R&D are in effect always significant for USPTO patents, whereas the current R&D component of the overall R&D elasticity of patents gets a positive and significant coefficient for both USPTO and WIPO patents but not for EPO. The coefficient of squared R&D is always negative.

This tells us that R&D is subject to decreasing returns: as R&D expenditures increase, the number of patents increases at first, but then turns negative beyond a certain threshold. 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 get a positive and statistically significant coefficient, along with firm size and the dummy for EU firms. For both USPTO and WIPO patents also current R&D and current capital expenditures are positive and significant, whereas the same finding of the basic Poisson model is found in relation to the squared term of both variables.

Columns IV present the estimates of the negative binomial model, that has been shown in the previous section (cf. figure 2 above) to be our preferred specification. For patent applications with both EPO and USPTO current capital expenditures are positive and significant, along with lagged R&D for EPO patents and R&D lagged by 1 and 2 periods for 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)
$\ln(CapExp)_{t-1}$	-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%

In the case of WIPO patents, among the variables of interest only R&D lagged by 2 periods has a positive and statistically significant coefficient. The squared values of the capital expenditures variable are negative and significant with both the EPO and the USPTO data, to suggest a quadratic relationship between adoption of embodied technological change and creation of new patentable knowledge.

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)
$\ln(CapExp)_{t-1}$	-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	-
	-	0.0000	-	0.0000	-

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

Finally, the number of patents is always increasing along with firm size. Thus, at least with EPO and USPTO patent applications the finding with the *CapExp* variable are consistent with our hypothesis that the adoption of improved machinery and capital equipment may play a crucial role in the final stage of development of new patentable items, likely closer to market exploitation than those made possible by R&D

expenditures. This implies complementarity rather than substitutability between R&D and capital expenditures in a science-based industry. In this connection, one may argue that crucial for obtaining patentable inventions is not only the firm's ability to discover and invent, but also its investments in capital equipment with embodied technological change. The hypothesis is consistent with the findings by Hall and Ziedonis[10] (2001) for the case of semiconductors, showing that also in science-based industries capital investments may exert an important effect on the propensity to patent, even larger than that of R&D spending.

The gamma specifications presented in column V give results that corroborate those of the negative binomial model. The main differences arise in the regression using USPTO patents: the coefficients of both the *Emp* and the $CapExp^2$ variables are no longer statistically significant; whereas the coefficient of the dummy variable for EU firms turns significant (even though only at a 10% confidence level).

5. Conclusions

This paper analyzes the impact of current, lagged, and squared expenditures on in-house R&D and the purchase of new machinery and capital equipment on the knowledge output generated by a sample of firms in the biotechnology industry. Findings point out that for patent applications with EPO both current capital and R&D expenditures are positive and significant. Conversely, with USPTO patents the main determinant of new patent applications is R&D lagged by 1 and 2 periods. In the case of WIPO patents, among the variables of interest only R&D lagged by 2 periods is positive and significant. The squared values of the capital expenditures variable are negative and significant with both the EPO and the USPTO data, to suggest a quadratic relationship between adoption of embodied technological change and creation of new patentable knowledge. Finally, the number of patents is always increasing along with firm size.

These results are consistent with neither the assumption of constant returns to scale in R&D, nor with that of a decline in R&D productivity. What they demonstrate in a clear fashion is instead that R&D and capital expenditures are to a significant extent complementary forces and determinants of the innovation process. Even in a science-

[10] Even though they use a stock measure such as *capital intensity*, i.e. the capital-labor ratio.

based industry such as biotechnology. This finding is consistent with the hypothesis that biotechnology is shifting from an “entrepreneurial technological regime” to a routinized technological regime”: whereas in the former R&D activities are the main and sometimes sole input to the overall innovation process, in the latter thanks to innovation-specific capital expenditures the entire procedure becomes more focused. Should this finding be confirmed by case-studies and qualitative evidence on the organization of innovative activities, one may conclude that biotech firms will be worth spending the money they devote to the creation of patentable knowledge in a well balanced mix of direct and indirect sources of innovation, embodied technological change included, rather than simply spending more and more in R&D. As a consequence, innovation policies and policy aimed at promoting the emergence of science-based industries should pay more attention to the support of firms’ investment in new machinery and capital equipment. Also considering that firms in this industry have been shown to rely mostly on internal funding sources for innovation, with a tiny minority of them able to attract external funding (Patel et al., 2008).

In sum, findings in this paper allows us to change the question raised in the title into a straight statement: *The better you spend, the more (patentable inventions and discoveries) you get*.

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