Paper to be presented at the

35th DRUID Celebration Conference 2013, Barcelona, Spain, June 17-19

Patents and R&D at the Firm Level: A panel data analysis applied to the Dutch pharmaceutical sector

Shreosi Sanyal
Hasselt University
Economics
shreosi.sanyal@uhasselt.be

Mark Vancauteren
Hasselt University
Economics
mark.vancauteren@uhasselt.be

Abstract

This paper analyzes the effect of research and development (R&D) intensity and other economic determinants on the innovation output of the Dutch pharmaceutical sector. A dynamic count data model is developed and applied, in the context of panel data framework (following Wooldridge, 2005). Our model incorporates the R&D intensity and other firm characteristics as explanatory variables. Although, both patent counts and citation-weighted patents can be viewed as indicators of technological impact and information flow, the latter reflects the quality of the patents. Hence, we consider both patent counts and citation counts, also for EPO and USPTO patents individually, as the innovation output indicator. From the estimated results, it is found that the R&D efforts have a positive and significant impact on both the patent counts and citation-weighted patents. This confirms the fact that, R&D acts as a major determinant for generating new patents. Concerning the role played by firm size, there seems to be a positive and significant relation between innovation output and size of the firms. But the significance becomes less prominent when we allow for random effects. Age of firms seems to have a negative and significant relation with innovation output. This signifies the fact that young firms are more enterprising, and are more innovation prone. Our model is further extended by incorporating dynamics, whereby it is observed that Dutch Pharmaceutical firms innovate persistently over time. This phenomenon is prominent for both patent counts and citation-weighted patent counts.

Jelcodes:C51,C13

Patents and R&D at the Firm Level: A panel data analysis applied to the Dutch pharmaceutical sector

ABSTRACT

This paper analyzes the effect of research and development (R&D) intensity and other economic determinants on the innovation output of the Dutch pharmaceutical sector. A dynamic count data model is developed and applied, in the context of panel data framework (following Wooldridge, 2005). Our model incorporates the R&D intensity and other firm characteristics as explanatory variables. Although, both patent counts and citation-weighted patents can be viewed as indicators of technological impact and information flow, the latter reflects the quality of the patents. Hence, we consider both patent counts and citation counts, also for EPO and USPTO patents individually, as the innovation output indicator. From the estimated results, it is found that the R&D efforts have a positive and significant impact on both the patent counts and citation-weighted patents. This confirms the fact that, R&D acts as a major determinant for generating new patents. Concerning the role played by firm size, there seems to be a positive and significant relation between innovation output and size of the firms. But the significance becomes less prominent when we allow for random effects. Age of firms seems to have a negative and significant relation with innovation output. This signifies the fact that young firms are more enterprising, and are more innovation prone. Our model is further extended by incorporating dynamics, whereby it is observed that Dutch Pharmaceutical firms innovate persistently over time. This phenomenon is prominent for both patent counts and citation-weighted patent counts.

1 INTRODUCTION

Although, both R&D and patents are used as indicators of technological capacity of firms, it has often been recognized that the measures capture different aspects of the innovation process. While R&D expenditure can be viewed as a measure of the resources devoted to innovation, patents reflect the results of the innovation processes. Different innovation output indicators include patents, innovative sales, innovation counts or product information. But patents are widely used as a proxy for innovation output, as it is more appropriate for our study, based on the innovation intensive pharmaceutical industry. The quality and availability of the data on R&D and patents has improved and refined in the recent years. Computerization of patent offices and regular surveys of R&D activities allows researchers to perform detailed analysis of Patent-R&D relations. Therefore, we attempt to analytically and quantitatively clarify the contemporaneous relation between patenting and R&D expenditures at the firm level using a panel data framework.

Patent has always been recognized as a rich and potentially fruitful source of data for the study of innovation and technical change. Patent data is particularly pertinent for studying pharmaceuticals because drugs are one category of innovation where the incentive-giving role of patents works best, given the considerable investments they require. The pharmaceutical industry is intensively research oriented, performing various innovation activities consistently. Levin *et al.* (1987) showed that a patent is the most effective method to appropriate returns in industries with chemical base, such as pharmaceuticals. This in turn enables them to recover the R&D investment.

In recent literatures, citations weighted patents are mostly used instead of simple patent counts. Patent citations allow one to study spillovers, and to create indicators of the "importance" of individual patents, thus introducing a way of capturing the enormous heterogeneity in the “value” of patents. Innovations vary extensively in their technological and economic importance and significance. Moreover the distribution of such “importance” or “value” is highly skewed. In the works of Schankerman and Pakes (1986) and, Pakes and Simpson(1991), patent renewal data is used, which clearly revealed this drawback of simple patent count data. In our analysis, we focus and deal with the citation weighted patents, in addition with simple patent counts, as innovation output indicators.

Forward citation counts is generally used to denote citation-weighted patents. If a patent receives citations from other future patents, this is an indication that it has contributed to the state of the art. In other words, a generality score suggests that the patent most likely had a widespread impact, influencing subsequent innovations in a variety of fields. Hence the term “generality” is labeled on forward citation weighted patents. “Originality” of citation weighted patents is defined in a similar way, except that it refers to citations made. Thus if a patent cites previous patents that belong to a narrow set of technologies, then the originality score will be low. Similarly, citing patents in a wide range of fields would render a high score. Earlier studies have shown that forward citations are positively correlated with the monetary value of the patent (Harhoff et al., 1999; Lanjouw and Schankerman, 2001; Trajtenberg, 1990), which clearly reveals the fact that forward citations act as a barometer for determining the worth of the patents. Based on the study by Hall *et al.* (2005), the pharmaceutical sector has distinct characteristics of discrete product technologies where patents perform the traditional role of exclusion, and citations measure their value on an individual basis.

In this paper, we implement statistical models of counts (non-negative integers) in the context of panel data, in order to analyze the relationship between patents and R&D expenditures. The model used is an application and generalization of the Poisson distribution to allow for independent variables, persistent individuals (fixed or random effects) and noise or randomness in the Poisson probability function. In addition, our panel data allows us to analyze the relation between past innovation activities to current innovation activities. Consequently, this helps us to comprehend if there exists a persistence in innovation at the firm level. Since innovation is concomitant to firm’s growth, permanent asymmetries in productivity can be due to permanent differences in innovation. In general, micro level studies that look at the dynamics of patent-R&D relationship show evidence of the persistence in innovation (for example, Van Leeuwen, 2002).

As posited by Peters (2007), a couple of reasons can be cited for firms to innovate persistently. Firstly, the dynamics of a firm’s innovation behavior is an essential assumption for endogenous growth models, that rationalize the idea of intertemporal complementarity in innovation. Secondly, the so-called “success breeds success hypothesis” assumes that firms become more prosperous through successful innovation, due to broader technological opportunities. Finally, some theoretical explanations consider the sunk costs in R&D investments as an important source of persistence since they create barriers to entry, causing engagements to continue innovation. It is observed that the pharmaceutical sector, which is primarily based on knowledge, is more susceptible to technological accumulation or pioneering in persistence in innovation, compared to other industries. Also, the innovative pharmaceutical firms has the tendency to patent their inventions steadily, even by marginally changing their past innovations, so that they can ward off unwanted competitors or imitators.

Therefore, apart from identifying the relation between R&D expenditure and innovation output, the contribution of the study is two-fold. Firstly, our panel data allows us to analyze the dynamics of the innovation process. In other words, it enables us to find whether past innovation activities affect current innovation activities. Secondly, our study pioneers in studying the innovation input-output relation of the pharmaceutical sector in the Netherlands at a detailed and comprehensive level. Also, our intensive dataset provides us with information on whether the patents are applied at the US or European patent offices. This allows us to draw inferences on national and international patenting activities.

The remainder of the paper proceeds as follows. Sections 2 provides a quick review of the literature dealing with R&D-patent relationship. Section 3 offers a brief overview of the methodological underpinnings of the empirical model. Section 4 describes the data used in our model. The empirical findings of different versions of the model explaining innovation activities are then discussed and contrasted in section 5. Finally, section 6 concludes.

1.1 A brief description of EPO versus USPTO patents

Patents and their citations are largely used to measure knowledge spillover from the R&D activities of the firms. But there lies prominent institutional differences in the process of governing the decision of granting a patent, or including a patent citation in a patent document. Although a few aspects of patent law has been harmonized internationally, there still remains a number of important differences between them. Since, in our analysis, we consider both EPO and USPTO patents, we try to take a closer look at the differences between them in this subsection.

The first difference between the EPO and USPTO patents are the priorities given when two candidates apply for a patent for the same invention. In case of EPO patents, the only thing that counts is the filing date. The first candidate to have filed his application will get the patent, even if the second candidate had come up with the invention first. But in the USA, a determination is made as to who invented it first. This usually involves examining laboratory logbooks, establishing dates for prototypes etc. So even if a person filed a patent later but is found to have invented earlier, he may be awarded a USPTO patent.

The second prominent difference is that, US patent law requires that the inventor include the best way to practice the invention in the patent application, which bars him from keeping essential or advantageous aspect a secret. In contrary, European patent law has no such requirement. It only requires that at least one way of practicing the invention needs to be included in the application. But it does not focus on the fact whether the invention used is the best way or not.

The difference in the grace period is the third important distinction between them. In case of EPO patents, if the invention has become publicly available (like selling the invention, giving a lecture about it, or showing it to an investor without a non-disclosure agreement), the patent application will be rejected. It does not make any difference whether the person making it publicly available is the inventor, one of the inventors or an independent third party. But for USPTO patents, a one year grace period is provided, which implies that the inventor can freely publish his invention without losing the patent rights.

Fourthly, the US patent law is a federal statute. Since a US patent is a property right which is enforceable in the entire territory of the USA, it allows patent holder to prevent anyone from making, using or selling in the USA the patented invention. In contrast, the European Patent Convention is a treaty signed by the twenty-seven European countries. As a granted European patent under the EPC confers to its owner the same right as a national patent in those EPC countries he elected in the application; a European patent once granted can only be annulled by separate proceedings in each elected country.

The invention procedure is the fifth difference between the two systems. Although both EPO and USPTO requires that an invention be novel and requires an inventive step, EPO has a more strict interpretation of this term. A European patent application involves an inventive step if it solves a technical problem in a non-obvious way.

Also, there are relevant differences between citation practices in the USPTO and EPO. The US patent office follows the ‘duty of candor’ rule which imposes all applicants to disclose all the prior art they are aware of. Hence, many citations at the USPTO come directly from inventors and applicants and finally filtered by patent examiners. But the European Patent office follows no such rules. For the European patents, the patent examiners draft their report, trying to include all the technically relevant information within a minimum number of citations (Michel and Bettels, 2001). Hence, EPO patent citations are usually added by the examiners. Consequently, the analysis of diffusion and obsolescence of technological knowledge and knowledge spillovers may reveal different properties according to the used patent dataset.

The final concomitant distinguishing feature between the two kinds of patents is the two-part claims. European patent applications virtually always has a two-part claim. The latter features are those that constitute the invention. The former features are found in the prior art. If an application is filed with one-part claims, the foremost thing that happens is that the Examiner identifies the closest prior art and requests that the claim be delimited there from. On the contrary, a US patent application always have one-part claims. If there exists a two-part claim in a US patent, chances are that the patent is owned by a European firm.

2 LITERATURE SURVEY

Very few studies seek to analyze a relation between patents and R&D at the microeconomic level, inspite of the fact that, both the indicators are commonly used to analyze technical change. For measuring the relation between innovation expenditures and innovation output, the econometric models were developed by Griliches (1979) and Crepon *et al*. (1998). In the work of Griliches (1979), innovation performance relation was divided into three equations, where the second equation, that is, the knowledge production function, relates innovation inputs to innovation output.

According to Klomp and Van Leeuwen (1999), firms that perform R&D on a continuous basis shows a significantly higher innovation output. Lööf and Heshmati (2000), while focusing on the relation between expenditures on innovation input and its effect on innovation output, found that the most important source of knowledge comes from within the firm, whereas competitors are the most important external source of knowledge.

Mairesse and Mohnen (2005) found that innovation output is generally more sensitive to R&D in low-tech sectors than in high-tech sectors.

A panel data analysis of knowledge production function was initiated by Pakes and Griliches (1980), who defined a theoretical model relating innovation input to innovation output. They derived a distributed lag regression, where the number of patents was regressed on current and five lags of R&D and firm individual effects. In their specification they ignored the discreteness of the patent data and used the 'within' estimator to account for individual effects. Pointing out the limitation of this study, Hausman *et al*. (1984) proposed a number of panel data models in order to estimate the patent-R&D relationship that took into account the discreteness of the patents, namely the fixed effect and the random effect Poisson and negative binomial regressions.

Count data models are applied to the patent-R&D relationship by a number of researchers, which includes Bound *et al*. (1984), Hausman *et al.* (1984) and Crépon *et al*. (1996). The application of the CDM model can be found in a number of recent empirical studies that include Griffith *et al.(*2006), Mohnen *et al*.(2006), Polder *et al*. (2009), Hall *et al*. (2009) and Raymond *et al*. (2009).

Though innovation is an inherently dynamic process between heterogeneous firms, most empirical studies conclude that there is no strong and clear cut evidence of persistence in innovation activities. Montalvo (1997) referred to possible simultaneity problems in the relationship between Patents and R&D. The previously employed count model were based on strict exogeneity of the expenditure in R&D with respect to patents. However, once a patent is granted, the firms may need to invest in R&D in order to transform the patent into a more commercial innovation for obtaining benefits. From this viewpoint R&D is used as a predetermined variable rather than being strictly exogenous.

But Peters (2009) finds a strong persistence in innovation input, both in terms of R&D or non-R&D innovation expenditure, as well as in terms of new products or processes in the market. Also Peters (2007) infers that success breeds success, as the past share of innovative sales influences positively the probability of innovating in the future. Based on the work of Duguet and Monjon (2004), there exists a strong persistence of innovation at the firm level, provided that the theoretical modeling is based on the firm size. Both Roper and Dundas (2008) and Antonelli *et al.* (2010) confirmed on the persistence of innovation, focusing on the Irish Innovative Panel and the Italian manufacturing firms respectively.

But, according to the earlier finding of Geroski *et al*. (1997), larger firms innovate steadily over a period of time. But this happens till a threshold level, beyond which, firms fail to innovate persistently. Thus firm size plays a significant role on innovation persistence. However, as pointed out by Cefis and Orsenigo (2001), although persistence seems to increase with firm size, the relation is rather sector specific and country specific. Also, the absence of innovativeness can be due to turbulence in a sector, as measured by the Entry and Exit of firms (Malerba and Orsenigo, 1996).

Among the other determinants, firms size may affect the marginal costs of patent application. The cost per patent application for small firms are expected to be higher than large firms since most of the small firms neither have a specialized unit dealing with patents nor property rights. Also they do not have detailed prior information about the patent system. In addition, it is argued that small firms hesitate to apply for patents because of the large patent litigation cost (Cohen and Klepper, 1996) . But, in sharp contrast, empirical studies (like, Acs and Audretsch, 1991; and Pavitt *et al*., 1987), have found that, small firms tend to innovate comparatively more.

We estimate our model by using econometric methods that can deal with the different problems inherent in the model and related to the nature of the data. Most studies on innovation are potentially affected by selectivity biases. In case of patent data, relatively few firms have patents and hence, analyses limited to them may be biased. As stressed by Mairesse and Mohnen (2010), the R&D-innovation framework has been extended in various directions as the use of innovation expenditures rather than the use of R&D expenditures (Janz *et al*., 2004, and Lööf and Heshmati, 2006), by including a demand shifting effect of innovation output (Klomp and van Leeuwen, 2006), making a distinction between new-to-firm versus new-to-market innovations (Duguet, 2006), and using other determinants along with R&D as innovation inputs (physical capital investment for process innovation in Parisi *et al*., 2006, and Hall *et al*., 2009, and ICT in Polder *et al*., 2009).

3 EMPIRICAL IMPLEMENTATION

We focus on adopting statistical models of counts (non-negative integers) in the context of panel data and using them to analyze the relationship between patents and R&D expenditures. Count outcomes are often characterized by a large proportion of zeroes. Although linear and logistic models have often been used to analyze count outcomes, the resulting estimates are likely to be inefficient, inconsistent and biased. The model used in this paper is adapted to a panel data framework, where R&D availability is not necessarily a prerequisite. Examples of empirical studies that uses similar R&D selection criterion, in a cross-sectional dimension, are given by Griffith et al. (2006), Klomp and Van Leeuwen (2006) and Hall et al. (2009). The patent count data is fully observed in our sample and consists of patents from United States (USPTO= U.S. Patent and Trademark office) and Europe (EPO=European Patent Office). Our model is an application and generalization of the Poisson distribution to allow for independent variables, persistent individuals (fixed and random effects) and noise or randomness in the Poisson probability function.

Since patent data is discrete, it motivates us to use the count model (Nesta and Saviotti, 2005). But since many firms have zero patent counts, we estimate the innovation output using a zero inflated count model. The zero inflated count model allows for the unobserved heterogeneity by means of random effects.

3.1 The Patent Equation

Our empirical model explains the innovation output, which is measured by the number of patents filed in a given year, in terms of R&D- patent relationship. We use a count model because of the discreteness of patent data (Nesta and Saviotti, 2005). Due to problems in R&D expenditures or uncertainty in the market, firms can decide not to patent. Hence, it is to be noted that, there are many firms in our data which are never granted any patent for the entire sample period or consequently, there are several zero patent counts in our patent data. To take this excess of zeroes into account, we estimate the patent equation using a zero- inflated count model. Zero-inflated count model has been used in the works of Hall (2000) and Min and Agresti (2005), allowing for unobserved heterogeneity by means of random effects. Let,

$$P_0(y, \lambda_{it}) \equiv \exp(-\lambda_{it})\lambda_{it}^{y} / y! \tag{1}$$

where λ_{it} is the Poisson distribution parameter and $y \in \{0,1,2,...\}$. The random zero inflated Poisson model (ZIP) can be written as,

$$\Pr(PAT_{it} = y) = (1 - p_{it})P_0(y_{it}, 0) + p_{it}P_0(y_{it}, \lambda_{it}) \tag{2}$$

where PAT_{it} is the number of patents for firm i at time t, $1-p_{it}$ represents the probability of extra zeroes. We model $\ln\lambda_{it}$ as,

$$\ln\lambda_{it} = (a_{3i} + \gamma R\&D_{it} + \beta_3^{'}x_{1it}) \tag{3}$$

where a_{3i} is a time-invariant unobserved firm effect and, x_{1it} is the vector of additional independent variables that includes the log of the number of employees (e_{it}), age of the firms (a_{it}), time dummies (α_k), entry dummies(β_k) and exit dummies(γ_k).

Firm size measured by the number of employees reflects access to better financing (Mairesse and Mohnen, 2002). The size of firms is log- transformed in the estimation. We also introduce the variable age, which is likely to shed light on the dynamics of the industries. The technology and products of industries evolve according to the innovations that are introduced as entrant, surviving and incumbent firms. Papers like Audretsch (1995) and Klepper (1996) provide theoretical insights into the nature of this dynamics. Entry and exit dummies are incorporated in order to analyze how survival mechanisms affect heterogeneous mechanisms of innovation and growth.

In case of firm's unobserved $R\&D_{it}$, we consider its predicted values. The selection criterion for the panel data is such that we use data on firms that report R&D and compute the predicted R&D for those firms which do not report their R&D effort. We then calculate the effect of R&D on patents for all firms. In this framework we assume that the effect of no-R&D reporting firm is the same as R&D reporting firms. Since we distinguish between zero R&D and non-reporting R&D, we also assume that some non-innovating firms maybe R&D performers.

We use the zero-inflated negative binomial (ZINB) distribution, where PAT_{it} can be modeled as follows:

$$P_0(y,\lambda_{it}) = \frac{\Gamma(\alpha^{-1}+y)}{\Gamma(\alpha^{-1})+\Gamma(1+y)}\left(\frac{\alpha^{-1}}{\alpha^{-1}+\lambda_{it}}\right)^{\alpha^{-1}}\left(\frac{\lambda_{it}}{\alpha^{-1}+\lambda_{it}}\right)^{y} \tag{4}$$

where $\Gamma(.)$ denotes the gamma function. This model is particularly suited for overdispersed data. It reduces to ZIP when α=0.

In our random effect zero inflated count models, the random effects are assumed to be standard normal variables multiplied by standard normal probability density function that enters the log-likelihood function. The log likelihood for the zero inflated count model with random effects is given by,

$$\log L = \sum_i \log \phi(b_i) + \sum_i \sum_t z_{it} \log(p_{it}) + (1 - z_{it}) \log(1 - p_{it})$$
$$+ z_{it} \log[P_0\{PAT_{it}, \exp(a_{3i} + \gamma R\&D_{it} + \beta_3' x_{1it})\}] \tag{5}$$

where ϕ is the standard normal probability density function and, z_{it} is an indicator variable which is equal to 1 if $PAT_{it} > 0$, and 0 if $PAT_{it} = 0$.

In our analysis we test the statistical properties of various count data models and adopt a zero-inflated negative binomial model that takes into account the unobserved heterogeneity with respect to the propensity to patent and the ability of firms to generate inventions (Cincera, 1997).

3.2 Extension to Dynamics

In our analysis, we extend the model to a dynamic framework. The richness of our panel data enables us to analyze the dynamics of the innovation process. With specific reference to Netherlands, existing studies that have investigated the dynamics of the relationship between R&D and patenting activity include Van Leeuwen (2002) and Raymond *et al.* (2009). Both studies confirm persistence of innovation. Firms may innovate persistently for a number of reasons. In the “Success breeds Success” hypothesis firms become more prominent because of innovation due to broader technological opportunities. Consequently accumulation of knowledge would induce state dependence invention flows and hence, persistence of innovation. Another theoretical reasoning considers the sunk costs in R&D investments as a predominant source for steady innovation as they create entry barriers and hence, engagements to continue innovation.

In our model, we analyze whether firms exhibit persistence in innovation by using lagged patents and patent dummies for the past years, within the concerned time frame of our model. Using patent lags and patent dummies might throw some light on individual firm in their propensity to patent. The requirement to allow for such individual effects eliminates much of the variance in the available short time series framework.

Hence, our basic model (eq. 3) gets transformed to:

$$\ln\lambda_{it} = (a_{3i} + \gamma R\&D_{it} + \beta_3^{'}x_{1it} + PAT_{it-1} + PAT_{it-2} + ... + PAT_{it-n} + PATdummy) \qquad (6)$$

where, $(PAT_{it-1}, PAT_{it-2}, PAT_{it-n})$ denotes the lagged patents till year n (in our model n=10), and $PATdummy$ denotes the patent dummy. Therefore, in our model, we introduce the fact that, the propensity to patent in the current year depends on the past history of patenting for the individual firms. Additionally, we measure persistence using a lagged patent dummy, where each firms who has patented atleast once in their past period is assigned a value of 1, and zero otherwise.

4 DATA DESCRIPTION

Our study is based on an unbalanced panel data set for the period 1996-2006. We obtained 673 pharmaceutical firms that are extracted from the Statistics on Financial Enterprises provided by the Central Bureau of Statistics (CBS) and the REACH database (Manufacturing of Pharmaceutical products and Pharmaceutical preparations, NACE Rev.2 Code 21).

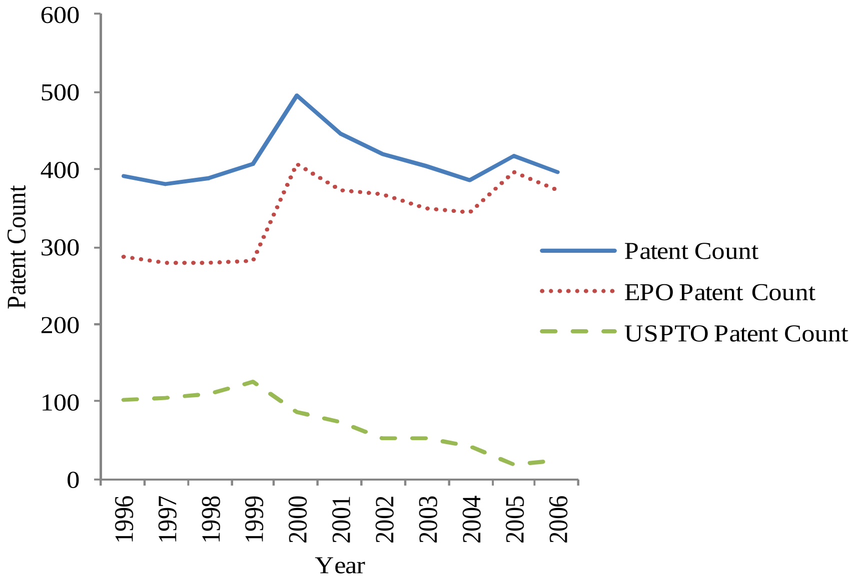
The ownership criteria are essential in the construction of our sample. Since firms register patents or report R&D expenditures under different names, we used the Algemeen Bedrijven Register (ABR=general business register) data, issued yearly by Statistics Netherlands on firms' ownership structure, to find the names and the direct ownership (expressed in percentage) of all their subsidiaries, holding units, and their shareholders. We manually assigned a Chamber of Commerce (KvK) code to each firm. Each KvK code was then electronically matched with a Statistics Netherlands internal code in order to obtain the entire ownership structure for each of the firms. By this selection, the number of pharmaceutical firms gets reduced to 520. In the sample of firms we define the possible (not necessarily ultimate) parent firm, which is necessarily located in the Netherlands and their data on input and output variables is available. To identify the (possible) ultimate parent, CBS takes into consideration a direct and indirect ownership of over 50%. It is noted that a considerable number of subsidiaries (daughters) were completely owned by a parent.

For each of the 520 firms, we looked at their entire ownership structure, including all possible subsidiaries (through an extensive manual search from the ABR), and subsequently matching them with patent counts from the patent database that has been made available by the Dutch Patent Office (Octrooicentrum, Netherlands). The patent data set from the Dutch patent office gives us information about indicators that include (besides other informations), the application number, the patent owner (name of the firm), patent title, name of the inventor, publication year, and location. The database comprises of all patents from the United States (issued by the USPTO) and Europe (issued by the EPO). The usefulness of this database is that, it eliminates any double counting of USPTO and EPO patents. All the respective firms (mother & daughters) from the ownership structure are matched manually by name with the patent database.

Also, we used a complementary database of the total population of European patents (issued by the EPO) for the period 2000-2006, that was partially made available from Statistics Netherlands. With this complementary database, we were able to double check the EPO patent counts for our firms with those that we obtained using the first database source. To calculate the number of forward citations, we consulted the PATSTAT database.

The innovative performance of the firms is indicated by patent counts and citation-weighted patent in our paper. In other words, patent act as the innovation output indicator in the innovation intensive Dutch Pharmaceutical sector. Due to the richness of our panel data, it was possible to perform analysis on not only the overall patents, but also on EPO and USPTO patents individually. As depicted in figure 1A, we find that there is a trend of gradual increase in the EPO patents over the concerned time period.

Fig 1A: Patent Counts for 1996-2006



It is evident from the diagram that the highest number of patents is in the year 2000, taking a downward trend for the next four years. But again after 2004, there is an increase in the number of patents for a year, until it takes a downturn in 2005. The EPO Patents counts show similar trends, due to the fact that, most of the overall patents constitutes the EPO patents. For the USPTO Patents, there is a gradual decline after 1999.

Fig 1B: Citation Counts for 1996- 2006

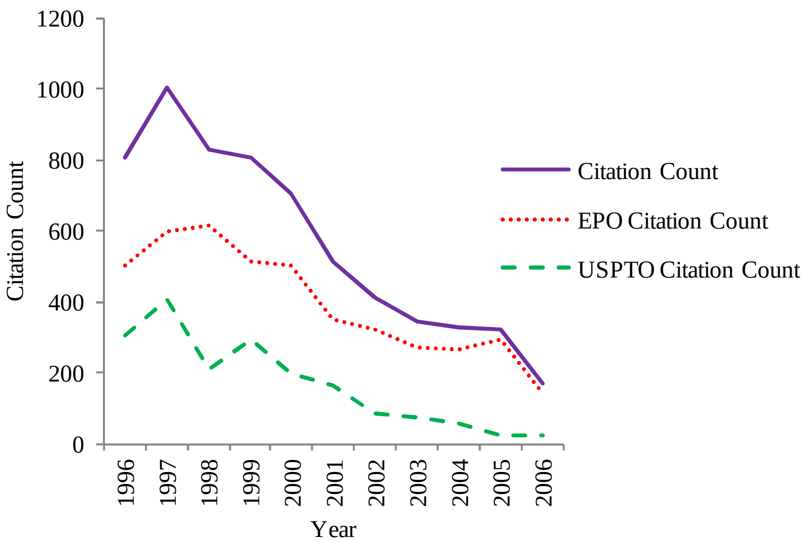


Figure 1B illustrates the trends in citation counts. The overall citation counts reaches its peak in 1997, after which it shows a downward trend in general.

The REACH database provides detailed financial data, ownership structure as well as information on their R&D expenditures for the TOP5000 largest Dutch firms (>100 employees). However, we find that in the database, only a small proportion of firms publish their R&D expenditures. This relates to the fact that for accounting purposes, many firms combine their R&D expenditure with other related costs (i.e., general and administrative expenses) under the heading intangible fixed assets or operational costs. The Dutch law that obligates firms to publish financial details (balance, profit and loss accounts, annual reports, ownership information), including their R&D expenditures, is applied to the TOP5000 firms. We used two complementary R&D data sources. We extract R&D data from the CIS waves (CIS2, CIS2.5, CIS3, CIS3.5 and CIS4) and R&D surveys that are collected by Statistics Netherlands. The R&D surveys report R&D expenditures in the odd years while each of the CIS waves measures R&D expenditures in the even years of our sample period. From the surveys we complemented R&D data for the 520 Pharmaceutical firms.

In the CDM model, R&D data availability is taken as a starting point, merely because the CIS data classifies innovating firms as those that generate both R&D and output innovation. Our approach allows us to exploit differences between innovators and non-innovators, both at the level of R&D expenditure and patent activities. A descriptive Statistics on R&D and patent behavior of sample firms is reported in Table 1. Our innovation data consists of 520 firms for every year during the period 1996-2006, after selection (which is based on the ownership structure of the firm). Among the 520 firms, 191 firms reported R&D. Similar statistics is carried out for all patenting firms, which includes the firms having EPO and(/or) USPTO patents.

Table 1: Innovation Data Sample

	R&D Reported	R&D Not Reported	Total
All Firms	191	329	520
Patenting Firms	44	28	72
Only EPO Firms	19	15	34
Only USPTO Firms	2	3	5
Both EPO and USPTO Firms	23	10	33
USPTO Patent Counts	613	188	801
EPO Patent Counts	3192	539	3731

It is evident from the table that, the total number of patents over the period 1996-2006 is 4532, with 3731 EPO patents and only 801 USPTO patents. Hence, an overwhelming majority of the Dutch patenting firms have used the European patent office, and not the patent office in US.

We also find that the total number of firms that patents is only 72 out of the 520 firms, wherein 44 patenting firms report R&D and 28 patenting firms does not report R&D. Therefore, a large group of pharmaceutical firms are not engaged in patent activities. Also, a majority of these firms can also be classified as non-R&D firms. As pointed by Licht and Zoz (2000), a large share of patents is applied by only a small number of firms and therefore the distribution of patent application among firms is highly skewed. Similarly, the number of pharmaceutical firms that reports R&D are much lesser than the number firms that does not report R&D.

It is surprising to note that, firms with patents sometimes do not report R&D. But this ambiguity can occur due to certain criterion followed while constructing the data file. Firstly companies sometimes report only the "material" R&D expenditure, and so the CIS waves or R&D survey may report R&D as zero (but not necessarily) if R&D expenditure is non-material. Alternatively, companies may say nothing about their R&D and keep their R&D expenditure as confidential. In such cases, R&D is reported as 'not available'. It is also likely that companies reported as "not available" include some which are randomly missing, that is, a company performs material R&D, but for some reason Statistics Netherlands could not accrue the data for a particular year or a given period.

Besides, R&D, the other explanatory variables included in our model are size of firms (measured by the number of employees), age of the firms and entry-exit barriers. They are extracted from the CBS database. We test for the effect of firm size on the propensity to patent by including the logarithm of the number of employees in our model. For estimation purpose, a log transformation has been used in order to allow for the skewness of the distribution. As the competitive conduct of firms changes prominently with the increase in the number of incumbents or with the exit of existing firms, we consider the entry and exit dummy. For those firms which has entered the pharmaceutical market within the concerned period is assigned 1 as the entry dummy and 0 otherwise. Similarly the exit dummy is calculated. The age of firms is measured as the difference between the entry year and the exit year of each of the firms for the successive years. We incorporate the age of firms as one of the control variables, owing to the fact that the life span of firms play an important role in determining the amount of its innovation output.

Innovation persistence is an important determinant for concentration of innovation activities of firms. We tried to capture the dynamics of the innovation process by incorporating lagged patents and lagged patent dummies as the explanatory variables. Patent lag is denoted by the number of patent for each firms in the past years. We further use a lagged patent dummy, which is 1 if a firm patents in the past years and zero otherwise. It is to be noted, in this context, that both firm size and entry-exit plays a major role in the innovation persistence of firms. Various empirical studies like Geroski *et al.* (1997) and; Duguet and Monjon (2004) stresses on the fact that, innovation persistence is influenced by size of firms. In addition, competitive turbulence, as defined by the entry-exit or survival of the firms, is significant for dynamics in innovation (e.g. Antonelli et al., 2010 and; Malerba and Orsenigo, 1996).

Table 2 represents the summary statistics of the variables used in our model.

Table 2: Descriptive Statistics

				<--------------------- Quantiles -------------->				
Variable	Obs	Mean	Std.Dev.	Min	0.25	Mdn	0.75	Max
Log (R&D per employee)	792	1.6	1.72	0	0.07	1.23	2.37	10.52
Patent Counts	5720	0.79	9.3	0	0	0	0	210
Citation-weighted Patents	5718	1.09	15.51	0	0	0	0	564
Log (Employment)	3880	2.87	2.46	0.69	0.69	2.08	4.2	10.19
Age	5676	9.33	11.9	0	0	3	16	39
Entry	5676	0.45	0.5	0	0	0	1	1
Exit	5676	0.46	0.5	0	0	0	1	1

5 EMPIRICAL ESTIMATION

5.1 Using simple patent counts as the dependent variable:

Our basic model incorporates the R&D intensity variable, which is the corresponding elasticity of the number of patents with respect to R&D, taken as its predicted value from the preferred Tobit II equation. The other independent variable that we consider in the basic model is the log of the number of employees (as a proxy for the size of firms). We further use age of the firms and entry-exit as additional regressors. Finally, dynamics is incorporated in the model by using a lagged patent dummy and lagged patent counts.

An important feature in the panel data application is the unobserved heterogeneity or individual fixed effects. We use maximum likelihood (ML) technique to estimate the model, following the approach recently proposed by Wooldridge (2005) for handling the individual effects. In this case, the distribution of the unobserved effects (a_{1i}) are modeled as follows: $a_{1i} = \alpha_{10} + (\delta_{10} R\,\&\,Dfitted)^{*}_{i0} + \delta_1' \bar{x}_{i1} + \xi_{1i}$, where α_{10} and α_{20} are constants, $\bar{x}_{i1}$ is the vector which includes the time averages of the variables $(e_{it}, s_{it}, l_{it})'$, $(R\,\&\,Dfitted)^{*}_{i0}$ and z_{i0} are the initial values, δ_{10} and δ_1' are the corresponding coefficients (vectors) to be estimated, and ξ_{1i} are assumed to be independent, following normal distributions $\xi_{1i} \mid x_{i1} \sim N(0, \sigma^2_{\xi 1})$.

We develop the model assuming random effects and excluding the initial conditions in our next estimation stage. However, full random effects is considered in the final estimations.

In this section, we use simple patent counts (overall, only EPO and only USPTO) as our dependent variable. To overcome the problem of excess zeroes, we have used the zero inflated negative binomial model. A Vuong test (Vuong, 1989) for each of the estimations, in order to discriminate between negative binomial (NB) and zero-inflated negative binomial (ZINB) models is applied. This test corrects for the complication that ZINB reduces to NB only at the boundary of the parameter space.

Table 3 provides the estimates of the patent equation. From table 3, we can find that model 1 and 2, does not have random effects and they reflect the basic models. The next five models allow for unobserved heterogeneity by means of random effects. We incorporate dynamics from regression model 4 onwards. Same regression techniques are used in the subsequent estimations with different regressands (as reported in table 4, 5 and 6).

It is observed that R&D intensity (as the fitted value) has positive and significant effect in most of the models (except Model 4 and 5). Hence, it turns out to be an important determinant in generating new knowledge. It is to be noted that, in case of Model 4 and 5, we have used the lagged patents as an additional regressor. Therefore, the insignificant impact of R&D intensity can be due to the problem of multicollinearity.

Concerning the role played by the size of firms, it is evident that larger firms have more tendency to patent. This confirms the empirical works of Cohen and Klepper (1996). Innovation involves significant start-up cost and economies of scope and scale. Hence, comparatively, large firms have a comparative edge over smaller firms. But the effect is significant when we do not allow for the unobserved heterogeneity.

Surprisingly, our results show the effect of age on patenting to be negative and significant in our models. As firm ages and establishes itself, other firms become more informed about the ability of the firm to succeed in innovation. Hence, the adverse effect of capital market imperfection increases over the larger firms. Therefore, we can conclude that younger firms are more innovation prone than their larger established counterparts. But the entry-exit dummy do not provide a conclusive result, probably due to the fact that the 11 years period of the firms' entry and exit into the market is too small to get a consolidated impact of them on the innovation output.

Table 3: ML-regression results for the patent equation using patent counts

Dependent Variable	Patent Counts	Patent Counts	Patent Counts	Patent Counts	Patent Counts	Patent Counts	Patent Counts
	ZINB Model 1	ZINB Model 2	ZINB Model 3	ZINB Model 4	ZINB Model 5	ZINB Model 6	ZINB Model 7
Log(R&D per employee)	0.26***	0.356***	0.163**	0.097	0.149***	0.07	0.178***
	[0.085]	[0.081]	[0.069]	[0.061]	[0.053]	[0.060]	[0.059]
Log(Employment)	0.494***	0.95***	0.199*	0.139	0.012	0.131	0.155*
	[0.047]	[0.061]	[0.113]	[0.091]	[0.098]	[0.089]	[0.089]
Age		-0.124***	-0.111***	-0.08***	-0.025*	-0.069***	-0.139***
		[0.014]	[0.018]	[0.017]	[0.013]	[0.016]	[0.018]
Entry		-0.352	-0.571	0.018	-0.991***	0.179	-1.633***
		[0.389]	[0.402]	[0.373]	[0.342]	[0.359]	[0.367]
Exit		-0.358	-0.631**	0.078	-0.934***	-0.153	0.461*
		[0.239]	[0.278]	[0.283]	[0.185]	[0.281]	[0.265]
Lag(Patent)				0.125***		0.192***	
				[0.022]		[0.027]	
Dummy(Patent)					-1.072***		2.637***
					[0.242]		[0.425]
Intercept	-2.63***	-3.344***	-3.177***	-4.162***	1.406***	-4.242***	-3.462***
	[0.612]	[0.602]	[0.648]	[0.650]	[0.538]	[0.622]	[0.610]
Initial(Patent)						-0.086***	0.029***
						[0.015]	[0.007]
Random Effect	NO	NO	YES	YES	YES	YES	YES
Log likelihood	-1583.740	-1546.390	-1511.891	-1394.779	-1345.259	-1381.692	-1458.707
N Observations	3868	3868	3868	3808	3868	3808	3868
Nonzero observations	274	274	274	262	274	262	274
Zero observations	3594	3594	3594	3546	3594	3546	3594

*** denotes 1% significance level, **denotes 5% significance level and *denotes 10% significance level

The positive and significant values for the lagged patents confirms persistence of innovation among firms. This proves that firms that patents in the past years have a strong tendency to patent in the following years, confirming the past literatures on the persistence of innovation. The lagged patent dummy appears to be negative and significant when we do not incorporate the initial conditions (in Model 5). With the incorporation of the initial condition in Model 7, the patent dummy appears to be positive and significant. Hence, Model 7 is our preferred model.

In table 4, we perform the same estimations as Model 3. But this time, we consider the EPO patent counts and the USPTO patent counts as the regressands. Model 6 and 7 are our reference model, where we allow for full random effect, by including both averages and initial conditions. Furthermore, dynamics is included in the last two models. Hence, for the estimations with the USPTO counts, we consider only model 6 and 7, for a comparative analysis with the EPO patents. The estimation results with EPO patents are found to be similar to that of Table 3. R&D intensity is positive and significant when EPO counts are used as the dependent variable. But, in case of USPTO counts, the coefficient for R&D intensity is negative and insignificant. A possible explanation is, very few firms in Netherlands apply for patents in US. Consequently, the number of patents from the US patent office is significantly less than the EPO patents, and hence do not capture the true picture of innovation output of the firms. Similarly, we find that, for firm size, the results using the USPTO patents provides a negative and insignificant result. But with the EPO patents, it is reconfirmed that, ceteris paribus, larger and well-established firms have a relative innovative advantage over the smaller firms. Age appears to be negative steadily and also significant in most of the cases, with or without allowing for the unobserved heterogeneity. But the results for entry-exit dummy appears to be inconclusive.

With the extension of our model to a dynamic framework, we find a positive and significant effect of patent lag, thereby proving again the concept of persistence of innovation at the micro level. Further, lagged patent dummy appears to be positive and significant for both EPO and USPTO patents, when initial conditions are applied. This confirms the results of Van Leeuwen (2002) and Raymond et al. (2009).

Table 4: ML-regression results for the patent equation using EPO and USPTO patent counts

Dependent Variable	EPO Patent Counts	EPO Patent Counts	EPO Patent Counts	EPO Patent Counts	EPO Patent Counts	EPO Patent Counts	EPO Patent Counts	USPTO Patent Counts	USPTO Patent Counts
	ZINB Model 1	ZINB Model 2	ZINB Model 3	ZINB Model 4	ZINB Model 5	ZINB Model 6	ZINB Model 7	ZINB Model 6	ZINB Model 7
Log(R&D per employee)	0.276***	0.34***	0.185***	0.099	0.157***	0.116*	0.183***	-0.165	-0.082
	[0.088]	[0.081]	[0.069]	[0.114]	[0.055]	[0.062]	[0.057]	[0.113]	[0.111]
Log(Employment)	0.486***	0.984***	0.251**	0.063	0.044	0.216**	0.169*	-0.192	-0.218
	[0.047]	[0.065]	[0.117]	[0.110]	[0.102]	[0.093]	[0.092]	[0.163]	[0.159]
Age		-0.129***	-0.108***	-0.087***	-0.02	-0.064***	-0.129***	-0.117***	-0.204***
		[0.014]	[0.018]	[0.022]	[0.013]	[0.017]	[0.019]	[0.024]	[0.033]
Entry		-0.411	-0.684	-1.11**	-1.05***	0.06	-1.945***	0.75	-1.665**
		[0.409]	[0.426]	[0.530]	[0.371]	[0.361]	[0.392]	[0.542]	[0.774]
Exit		-0.388	-0.658**	0.685	-0.965***	-0.044	0.578**	-0.28	0.236
		[0.25]	[0.282]	[0.501]	[0.193]	[0.298]	[0.255]	[0.390]	[0.474]
Lag(Patent)				0.069**		0.179***		0.225***	
				[0.034]		[0.028]		[0.034]	
Dummy(Patent)					-0.917***		2.444***		1.809**
					[0.262]		[0.419]		[0.743]
Intercept	-2.543***	-3.434***	-3.186***	-2.847*	1.266**	-4.332***	-3.046***	-7.182***	-2.193*
	[0.621]	[0.63]	[0.67]	[1.642]	[[0.571]	[0.656]	[0.639]	[0.883]	[1.169]
Initial(Patent)						-0.078***	0.029***	-0.149***	0.029***
						[0.015]	[0.005]	[0.024]	[0.006]
Random Effect	NO	NO	YES	YES	YES	YES	YES	YES	YES
Log likelihood	-1445.212	-1406.445	-1377.076	-1264.367	-1249.727	-1250.940	-1320.254	-534.589	-599.090
N Observations	3867	3867	3867	3807	3867	3807	3867	3808	3868
Nonzero observations	255	255	255	243	255	243	255	103	108
Zero observations	3612	3612	3612	3564	3612	3564	3612	3705	3760

*** denotes 1% significance level, **denotes 5% significance level and *denotes 10% significance level

5.1 Using citation weighted patent counts as the dependent variable:

The patent quality is proxied by the forward citation counts on each of the patents (based on empirical studies like Hall *et al.*, 2005). In this section, we focus and discuss on the effect of R&D intensity and other determinants on the citation-weighted patents. The results for overall citation weighted patents are enumerated in table 5.

Table 5: ML-regression results for the patent equation using citation-weighted patents

Dependent Variable	Forward Citation Counts	Forward Citation Counts	Forward Citation Counts	Forward Citation Counts	Forward Citation Counts	Forward Citation Counts	Forward Citation Counts
	ZINB Model 1	ZINB Model 2	ZINB Model 3	ZINB Model 4	ZINB Model 5	ZINB Model 6	ZINB Model 7
Log(R&D per employee)	0.437***	0.276***	0.076	-0.077	0.151*	-0.097	0.063
	[0.151]	[0.099]	[0.086]	[0.073]	[0.086]	[0.071]	[0.076]
Log(Employment)	0.307***	0.765***	0.049	-0.137	0.259*	-0.158	0.208*
	[0.074]	[0.097]	[0.150]	[0.108]	[0.135]	[0.110]	[0.126]
Age		-0.133***	-0.077**	-0.031	-0.101	-0.029	-0.114***
		[0.023]	[0.030]	[0.021]	[0.022]	[0.02]	[0.022]
Entry		-0.865*	-1.348***	-0.364	-1.444***	-0.269	-1.597***
		[0.499]	[0.510]	[0.454]	[0.433]	[0.455]	[0.454]
Exit		0.327	-0.454	-0.228	-0.827**	-0.308	-0.523
		[0.328]	[0.378]	[0.348]	[0.368]	[0.350]	[0.398]
Lag(Patent)				0.129***		0.183***	
				[0.026]		[0.033]	
Dummy(Patent)					3.198***		2.699***
					[0.600]		[0.587]
Intercept	-2.432***	-2.549***	-1.847*	-3.871***	-4.361***	-3.898***	-3.398***
	[0.765]	[0.798]	[1.106]	[0.616]	[0.767]	[0.603]	[0.870]
Initial(Patent)						-0.094***	0.024**
						[0.019]	[0.01]
Random Effect	NO	NO	YES	YES	YES	YES	YES
Log likelihood	-1530.424	-1509.203	-1481.990	-1381.926	-1459.823	-1373.352	-1451.056
N Observations	3866	3866	3866	3806	3866	3806	3866
Nonzero observations	240	240	240	229	240	229	240
Zero observations	3626	3626	3626	3577	3626	3577	3626

*** denotes 1% significance level, **denotes 5% significance level and *denotes 10% significance level

A positive and significant relation is observed between R&D intensity and patent citation when there is no random effect. But by allowing for random effect, we find an insignificant relation in most of the regression models. Similar results are observed for the coefficients obtained for the size of firms. However, the coefficients for both the independent variables are mostly positive, confirming a positive effect on citation-weighted patents. Coefficient for age is systematically negative, confirming our previous results. For the entry dummy, it is observed that, the coefficients are negative, though not always significant. Hence, the results suggests that more entrants causes lesser innovation output. Also with the exit dummy, we observe a negative relation in most of the cases. Entry-Exit causes turbulence in the market, which might affect the propensity to innovate, or, the quality of the innovation.

With the incorporation of dynamics, the regression results for both lagged patents and patent dummies are positive and significant. This again proves persistence in the innovation process. The intercepts are significant and negative for all the regression results.

Finally, we perform regression on the EPO and USPTO citation- weighted patents. The results are summarized in Table 6. Similar to the results obtained in table 5 for the overall patents, it is found that R&D intensity is positive and significant when random effects is not allowed. But with the estimation for USPTO citation- weighted patents, it is found that the estimation coefficients are significant and negative. Also, in case of the size of firms, the coefficients are positive and significant for the EPO citation counts for model 1 and 2. But when we allow for unobserved heterogeneity among the firms, the results are inconsistent for both EPO and USPTO Citations. A negative and significant impact of age on innovation performance again testifies that young firms are more enterprising and innovation prone. The coefficient for entry dummy is negative and significant in most of the regression results. However, the effect of entry dummy seems inconclusive. Again, innovation persistence is confirmed by positive and highly significant coefficients for lagged patents and lagged patent dummies for all the regression results, using EPO as well as USPTO citation- weighted patents.

Table 6: ML-regression results for the patent equation using EPO and USPTO citation- weighted patents

Dependent Variable	Forward EPO Citation Counts	Forward EPO Citation Counts	Forward EPO Citation Counts	Forward EPO Citation Counts	Forward EPO Citation Counts	Forward EPO Citation Counts	Forward EPO Citation Counts	Forward USPTO Citation Counts	Forward USPTO Citation Counts
	ZINB Model 1	ZINB Model 2	ZINB Model 3	ZINB Model 4	ZINB Model 5	ZINB Model 6	ZINB Model 7	ZINB Model 6	ZINB Model 7
Log(R&D per employee)	0.495***	0.318***	0.1	-0.074	0.158*	-0.067	0.042	-0.374***	-0.234*
	[0.149]	[0.113]	[0.079]	[0.070]	[0.081]	[0.071]	[0.075]	[0.145]	[0.136]
Log(Employment)	0.261***	0.791***	-0.085	-0.113	0.171	-0.189	0.056	-0.15	-0.122
	[0.070]	[0.100]	[0.152]	[0.137]	[0.141]	[0.126]	[0.170]	[0.183]	[0.21]
Age		-0.137***	-0.051**	-0.054**	-0.0816***	-0.009	-0.092***	-0.144***	-0.248***
		[0.023]	[0.022]	[0.026]	[0.0215]	[0.020]	[0.024]	[0.027]	[0.037]
Entry		-0.507	-1.573***	-1.147**	-1.701***	-0.144	-1.988***	0.64	-1.271
		[0.543]	[0.511]	[0.535]	[0.479]	[0.474]	[0.536]	[0.561]	[0.848]
Exit		0.282	-0.213	0.039	-0.791**	-0.061	-0.304	-0.694	0.296
		[0.355]	[0.334]	[0.388]	[0.368]	[0.36]	[0.410]	[0.448]	[0.569]
Lag(Patent)				0.034***		0.15***		0.313***	
				[0.012]		[0.033]		[0.046]	
Dummy(Patent)					3.231***		2.441***		1.466*
					[0.589]		[0.630]		[0.846]
Intercept	-2.202***	-2.856***	-1.612*	-1.532*	-4.307***	-4.104***	-2.809***	-7.66***	-1.242
	[0.734]	[0.874]	[0.968]	[0.937]	[0.763]	[0.633]	[1.03]	[0.998]	[1.472]
Initial(Patent)						-0.075***	0.024***	-0.255***	0.03***
						[0.019]	[0.008]	[0.043]	[0.008]
Random Effect	NO	NO	YES	YES	YES	YES	YES	YES	YES
Log likelihood	-1355.630	-1333.148	-1301.583	-1212.039	-1280.895	-1204.083	-1269.988	-606.887	-668.704
N Observations	3868	3868	3868	3808	3868	3808	3868	3808	3868
Nonzero observations	219	219	219	208	219	208	219	101	105
Zero observations	3649	3649	3649	3600	3649	3600	3649	3707	3763

*** denotes 1% significance level, **denotes 5% significance level and *denotes 10% significance level

6 CONCLUSION

Based on the empirical study, this paper revisits at the firm-level the effect of R&D intensity and other determinants on the innovation output of the firms for the Dutch Pharmaceutical industry. Considering the excess zero values for patents in our dataset, we performed count data analysis, using a zero- inflated negative binomial model.

From our analysis, R&D investment appears to have paid off when we consider simple patent counts as our innovation output indicator. However the effect appears to be insignificant when unobserved heterogeneity for each firm is applied for citation-weighted patents.

Further our analysis suggests that, large firms are more innovation intensive than smaller firms. However, the extent to which this occurs is decreasing in firm age. Large firms have more access to capital stock to engage in innovation. But at the same time, young firms are more enterprising. Our argument is that, the skill for patenting is unknown to the outsiders for young firms. But it is gradually revealed as the firm ages. The phenomenon is more intense when simple patent counts are used as our innovation output indicator. Moreover, the turbulence in innovation in the pharmaceutical market caused by the entry-exit and survival of firms might hinder the amount of patenting by the firms.

Finally, with the extension of our empirical model to a dynamic panel framework, the analysis that proceeded confirms the existence of a highly significant persistence in innovation. This characteristics of the Dutch Pharmaceutical firms are found to be consistent and strong in case of patents as well as citation-weighted patents.

Our analysis is done indepth, considering the regression results for both EPO and USPTO patents and citation-weighted patents individually, along with overall patents counts and their citation weightage. But the inconclusive results for major determinants, except for persistence, when citation- weighted patents are used allowing for random effects, needs to be further investigated.

REFERENCES

1. Acs, Z.J. and D.B. Audretsch (1987), "Innovation, Market Structure and Firm Size", *Review of Economics and Statistics* 69(4), pp. 567-574.
2. Antonelli, C., F. Crespi and G. Scellato (2010), "Inside Innovation Persistence: New evidence from Italian Micro- Data", *Laboratorio di economia dell' innovazione "Franco Momigliano", Universita di Torino, Italy,* Working Paper No. 10/2010.
3. Audretsch, D. (1995), "Innovation and Industry Evolution", *MIT Press.*
4. Bound, J., C. Cummins, Z. Griliches, H.B. Hall and A. Jaffe (1984), "Who does R&D and who Patents?",in *Griliches, Z. (ed.), R&D, Patents, and Productivity, Cambridge*, MA, pp. 21-54.
5. Cefis, E. and Orsenigo, L. (2001), "The Persistence of Innovative Activities: A Cross- Countries and Cross- Sectors Comparative Analysis," Research Policy 30(7), pp. 1139-1158.
6. Cincera, M. (1997), "Patents, R&D and Technological Spillovers at the Firm level: Some Evidence from Econometric Count Models for Panel Data", *Journal of Applied Econometrics* 12(3), pp. 265-280.
7. Cohen, W.M., and S. Klepper (1996), "A Reprise of Size and R&D", *The Economic Journal*, 106, pp. 925-951.
8. Crépon, B., E. Duguet and J. Mairesse (1998), "Research, Innovation, and Productivity: an Econometric Analysis at Firm Level", *Economics of Innovation and New Technology* 7, pp. 115-158.
9. Crépon, B. and E. Duguet (1996), "Innovation: Measurement, Returns and Competition", *INSEE studies*, No.1, pp. 83-96.
10. Duguet, E. (2006), "Innovation height, spillovers and TFP growth at the firm level: Evidence from French manufacturing", *Economics of Innovation and New Technology : Taylor and Francis Journals* 15 (4-5), pp. 415-442.
11. Duguet, E. and S. Monjon (2004), "Is Innovation Persistence at the Firm Level? An Econometric Examination Comparing the propensity Score and regression methods", *Cahiers de la Maison des Sciences Economiques, Universite Pantheon-Sorbonne, France*, Working Paper No. 04075.
12. Geroski, P. A., V.J. Reenen and C.F. Walters (1997), "How Persistently Do Firms Innovate?", *Research Policy* 26(1), pp. 33-48.

13. Griffith R., E. Huergo, J. Mairesse and B.Peters (2006), “Innovation and Productivity across four European Countries”, *Oxford Review of Economic Policy* 22, pp. 483-498.
14. Griliches, Z (1979), “Issues in assessing the contribution of research and development to productivity growth”, *Bell Journal of Economics* 10(1), pp. 92-116.
15. Hall, B., F. Lotti and J. Mairesse (2009), “Innovation and Productivity in SMEs: Empirical Evidence for Italy”, *Bance D. Italia*, Working Paper 718.
16. Hall,B., A. Jaffe and M. Trajtenberg (2005), “Market Value and Patent Citations”, *RAND Journal of Economics* 36, pp. 16- 38.
17. Hall, D. (2000), “Zero-Inflated Poisson and Binomial Regression with random Effects; A Case Study”, *Biometrics* 56, pp. 1030-1039.
18. Harhoff, D., F. Narin, F.M. Scherer and K. Vopel (1999), “Citation Frequency and the Value of Patented Innovation”, *Review of Economics and Statistics* 81(3), pp. 511-515.
19. Hausman, J., B. Hall and Z. Griliches (1984), “Econometric Models for Count Data with an Application to the Patents-R&D Relationship”, *Econometrica* 52, pp. 909-938.
20. Janz, N., H. Lööf and B. Peters (2004), “Innovation and Productivity in German and Swedish manufacturing firms- Is there a Common Story?”, *Problems and Perspectives in Management* 2, pp.184-204.
21. Klepper, S. (1996), “Entry, Exit, Growth and Innovation over the Product Life Cycle”, *American Economic Review* 86, pp. 562-583.
22. Klomp, L. and G.V. Leeuwen (2006), “On the Contribution of Innovation to Multifactor Productivity Growth”, *Economics of Innovation and New Technology* 15(4), pp. 367-390.
23. Klomp, L and G. van Leeuwen (1999), “The importance of innovation for firm performance”, *Statistics Netherlands*.
24. Lanjouw, J.O and M. Schankerman (2001), “Characteristics of Patent Litigation: A Window on Competition”, *The Rand Journal of Economics* 32(1), pp. 129-151.
25. Leeuwen, V. G. (2002), “Linking innovation to Productivity Growth using two waves of the Community Innovation Survey”, OECD Science, Technology and Industry Working Papers 2002/8, OECD Publishing.

26. Levin, R.C., A.K. Klevorick, R.R. Nelson and S.G. Winter (1987), “Appropriating the returns from industrial research and development”, *Brookings Papers on Economic Activity* 3, pp. 783-831.
27. Licht, G. and K. Zoz (2000), “Patents and R&D: An Econometric Investigation using Applications for German, European and US Patents by German Companies”, in: Encaoua, D; B. Hall, F. Laisney, J. Mairesse, *The Economics and Econometrics of Innovation*, pp. 307-338.
28. Lööf, H. and A. Heshmati (2006), “On the Relationship Between Innovation and Performance: A Sensitivity Analysis”, *Economics of Innovation and New Technology* 15(4/5), pp. 317-345.
29. Lööf, H. and A. Heshmati (2002),”Knowledge Capital and Performance Heterogeneity: A Firm-Level Innovation Study”, *International Journal of Production Economics* 76, pp. 61-85.
30. Mairesse, J. and P. Mohnen (2010), “Using innovation surveys for econometric analysis”, *UNU-MERIT Working Paper* 2010-023.
31. Mairesse, J. and P. Mohnen (2005), “The Importance of R&D for Innovation: A Reassessment Using French Survey Data”, *Journal of Technology Transfer* 30, pp. 183-197.
32. Mairesse, J. and P. Mohnen (2002), “Accounting for Innovation and Measuring Innovativeness: An Illustrative Framework and an Application, *American Economic Review* 92(2), pp. 226-230.
33. Malerba, F and L. Orsenigo (1996), “Schumpeterian Patterns of Innovation Are Technology- Specific”, *Research Policy* 25, pp. 451-478.
34. Michel, J and B. Bettels (2001), “Patent citation analysis: A closer look at the basic input data from patent search reports”, *Scientometrics 51*, pp. 185-201.
35. Min, Y. and A. Agresti (2005), “Random Effect Models for Repeated Measures of Zero- Inflated Count Data”, *Statistical Modeling* 5, pp. 1-19.
36. Mohnen, P., J. Mairesse and M. Dagenais (2006), “Innovativity: A Comparison across Seven European Countries”, *Economics of Innovation and New Technology* 15(4/5), pp. 391-413.
37. Montalvo, J.G (1997), “GMM estimation of count-panel-data models with fixed effects and predetermined instruments”, *Journal of Business and Economic Statistics* 15, pp. 82-89.

38. Nesta, L. and P. Saviotti (2005), “Coherence of the Knowledge Base and the Firm’s Innovative Performance: Evidence from the U.S. Pharmaceutical Industry”, *Journal of Industrial Economics* LIII(1), pp. 123-142.
39. Pakes, A and M. Simpson (1991), “The Analysis of Patent Renewal Data”, Brookings Papers on Economic Activity, Microeconomic Annual, pp. 331-401.
40. Pakes, A. and Z. Griliches (1980), “Patents and R&D at the Firm Level: A First Report”, *Economics Letters* 5 , pp. 377-381.
41. Parisi, M.L., F. Schiantarelli and A. Sembenelli (2006), “Productivity, Innovation and R&D: Micro Evidence for Italy”, *European Economic Review* 50(8), pp. 2037-2061.
42. Pavitt, K., M. Robson and J. Townsend (1987), “The Size Distribution of Innovating firms in the U.K: 1945- 1983”, *Journal of Industrial Economics* 35, pp. 297-316.
43. Peters, B. (2009), “Persistence of Innovation: Stylized Facts and Panel data Evidence”, *Journal of Technology Transfer* 34, pp. 226-243.
44. Peters, B. (2007), “Nothing’s Gonna Stop us Now? An Empirical Investigation on the Innovation Success Breeds Success’ Hypothesis”, *mimeo*.
45. Polder, M., G. V. Leeuwen, P. Mohnen and W. Raymond (2009), “Productivity Effects of Innovation Modes”, *Statistics Netherlands, Discussion Paper* 09033.
46. Raymond, W., P. Mohnen, P. Mohnen, P. Franz and S. V. Sybrand (2009), “Innovative Sales, R&D and Total Innovation Expenditures:Panel Evidence on their Dynamics”, *Cirano Scientific Series.*
47. Roper, S. and N.H. Dundas (2008), “Innovation Persistence: Survey and Case-Study Evidence”, *Research Policy* 37(1), pp. 149-162.
48. Schankerman, M and A. Pakes (1986), “Estimates of the Value of Patent Rights in European Countries during the Post-1950 Period”, *Economic Journal* 96, pp. 1052-1076.
49. Scherer, F. (1980), “Industrial Market Structure and Economic Performance”, *Rand McNally, Chicago*.
50. Trajtenberg, M. (1990), “ A Penny for Your Quotes: Patent Citations and the value of Innovations”, The Rand Journal of Economics 21(1), pp. 172-187.
51. Vuong, Q.H. (1989), “Likelihood Ratio Tests for Model Selection and Non-Nested Hypotheses”, *Econometrica* 57(2), pp. 307-333.

52. Wooldridge, J. (2005), “Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity”, *Journal of Applied Econometrics* 20, pp. 39-54.