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Persistence of Innovation, Technological Change and Quality-Adjusted Patents in the US Pharmaceutical Industry

Gautier DUFLOS

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PERSISTENCE OF INNOVATION, TECHNOLOGICAL CHANGE AND QUALITY-ADJUSTED PATENTS IN THE US PHARMACEUTICAL INDUSTRY*

Gautier DUFLOS[†]

CREST/LEI & Université de Paris I, Centre d'Economie de la Sorbonne - CNRS

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Abstract

This paper analyzes the American pharmaceutical firms' persistence in innovating prior to a wave of mergers and acquisitions that accompanied the "Biotech revolution". We evaluate the impact of past innovative activity on firms' innovation propensities using a non-linear GMM estimator for exponential models that allows for predetermined regressors and linear feedback. We find that innovative activity at the firm level strongly depends on the technological importance of past innovations. In particular this effect is likely to deter further pioneering behaviors rather than strengthen non cumulative R&D. Results also shed light on the importance of small firms in the technological development of pharmaceuticals, and suggest that large firms mainly persist in using patents possibly for strategic purpose.

Keywords: Patent Citations, Pharmaceutical Industry, Persistence in Innovation.

Ce papier analyse la persistance à innover des laboratoires pharmaceutiques Américains, antérieurement à la vague de fusions et acquisitions qui accompagna la "révolution des biotechnologies". Nous évaluons l'impact de l'activité passée d'innovation sur la propension courante à innover via des GMM non linéaires. Nous trouvons que l'activité d'innovation au niveau de la firme dépend fortement de la portée de son passé inventif. Plus particulièrement, les découvertes radicales dépendent fortement de la qualité des innovations passées de la firme et cet effet semble la détourner de comportement pionniers plutôt que l'inciter à poursuivre une recherche non cumulative. Les résultats montrent aussi que le niveau de l'activité et le pouvoir de marché des firmes sont négativement corrélés avec l'importance technologique des innovations faites et ne sont positivement corrélé qu'avec les dépôts brevets simples. Les petites firmes apparaissent alors être la principale source du changement technologique tandis que les firmes plus importantes semblent avoir moins d'influence et pourraient donc utiliser le brevet à des fins plus stratégiques.

Mots clés: Citations de Brevets, Industrie Pharmaceutique, Persistance à Innover.

JEL: O31, L12, C23.

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 $^{^{\}dagger}$ The author is also affiliated to PRISM-HEC. Contact adress: CREST-LEI Timbre J330, Ecole Nationale des Ponts et Chaussées ; 28, rue des Saints Pères - 75343 Paris cedex 07. E-mail: gautier.duflos@univ-paris1.fr

1 Introduction

Ever since Schumpeter's initial insights, the questions related to firms' efficiency and persistence in innovating have been a recurrent topic of interest. This literature emphasizes the two fundamental principles which are epitomized in the Schumpeter's "creative destruction" or "creative accumulation".² These two principles consider differently the relationship between economic domination and innovation activity. Which of these two principles dominates the other depends on the fundamental assumptions that are made concerning the properties of technology –specific to firms or equally accessible to everybody—and concerning the nature of innovative process—cumulative or not— (Ceffs, 2003). Basically the Schumpeter dynamics is such that innovation may lead to new technologies which undermine old monopolies' position although dominant firms may also benefit from history to innovate cumulatively.³ Accordingly, size and frequency of innovations are the fruit of two counteracting forces. On the one hand, the monopolist faces a "displacement effect" which indicates that firms with high market power will have no incentive to win a patent race too quickly as their current revenue streams will be displaced by an entirely new one.⁴ Indeed, entrants may have greater strategic incentives to invest in fundamental research leading to (radical) innovations.⁵ Nelson & Winter (1982) and Kamien & Schwartz (1982) labelled this pattern of innovative activity the "Schumpeter Mark I" in reference to what Schumpeter states in The Theory of Economic Development (1934). On the other hand, Gilbert & Newbery (1982) and Bud et al. (1993) argue that large firms are more likely to innovate persistently mainly because of an "efficiency effect". This effect reports the "persistence of monopoly" as being the extent to which leaders will spend more on pursuing innovation in order to maintain their dominance (e.g. Scherer, 1967). Dominant firms may also benefit from barriers to entry making them able to be persistent innovators as it is illustrated in the model of Segestrom & Zolnierek (1999). This pattern of innovative activity is also known as "Schumpeter Mark II" in reference to Capitalism, Socialism, and Democracy (1942).

¹See Scherer (1992), Pavitt (1988), Pavitt & Patel (1994) and Dosi (1988) for detailed discussions on this point.

²For a detailed analysis of these two Shumpeterian models of innovation see Scherer (1992) and Cefis (2001) mong others.

³Segestrom & Zolniereck (1999), for example, explain why industry leaders can often devote substantial resources to R&D by assuming they can improve their own products more easily than can other firms.

⁴See Arrow (1962), Reinganum (1982, 1983).

⁵Similar predictions are found in the organizational theory about the failure of incumbent firms to conduct radical innovation because of the diseconomies of R&D, inertia, complacency, etc., which makes harder to achieve returns to radical R&D (see Henderson, 1993).

The persistence in innovation is thus a key feature of the patterns of technological change. Despite the importance of this concern there is still few empirical evidences on both the firms' persistence in innovating and there innovations' quality. The aim of this research is thus to fill in this gap by analyzing the intra-firms technological dynamics of some US pharmaceuticals between the mid seventies and the nineties. Several questions are thus treated:

- i) How persistently firms innovate and with what scope?
- ii) Which firms influence the technological change?

Because innovation is often seen as a black box, this study relies on the use of patent and patent citation data as a better measure of firms' innovative activity.⁶ Patent citations makes it indeed possible to take into account both the influence and dependence which a given patent exerts on, and undergoes from, existing innovations. Such data are particularly pertinent for studying pharmaceuticals essentially because given the considerable investments they require, drugs are one category of innovation where the incentive-giving role of patents works best (Arora et al. 2001). Patenting in pharmaceuticals however remains also very heterogeneous in terms of technological importance and it is well known that pharmaceutical firms often rely on patents for anti-competitive practices, notably in order to face competition exerted by generics⁷ or by other research intensive firms.⁸ In pharmaceuticals innovators may thus take out hundreds of patents on marginal variations of the same basic invention, to erect a patent "fence" to keep unwanted competitors and imitators out (Davis, 2002).

The paper's contributions are twofold. Firstly, by identifying pioneering discoveries and assessing the firms' technological influence according to patent citation criteria (forward and backward citations), we evaluate in detail the firms' propensities to innovate (their inventiveness and their technological influence), conditional on their lagged R&D expenditures, internal spillover, amount of sales and market power then on their various patent stocks (i.e. accumulated knowledge). Secondly, we evaluate the feedback effects of past innovative activity on the current propensity to

⁶See Trajtenberg (1990), Hall et al. (2001) and Lanjouw & Schankerman (2002) for studies using patent citations.

⁷See Langinier (2001, 2004), Arundel & Patel (2003).

⁸See Lichtenberg & Philipson (2002) for an analysis on the different competitions ("between" and "whithin" patents) to which pharmaceutical firms face.

innovate to assess the role history plays in the firms' innovative behavior. Data on patenting and citations, in addition to firms' economic data, has been carefully gathered to obtain a unique unbalanced panel data for 77 traded innovating pharmaceutical firms for the period 1975-91.

Results indicate that innovative activities are rather persistent but strongly depend on the technological importance, or value, of past innovations. Most persistent innovative behaviors mainly concern those innovations having the poorest technological value. Conversely, the technological breakthroughs are likely to deter further pioneering behaviors in the short run rather than strengthen incentives to pursue investing in non cumulative R&D. The dynamic of innovation appears thus to be an important feature of innovative activity in pharmaceuticals. In addition, the firms' level of commercial activity and their market power appear to be negatively correlated with the technological influence of innovations. Small firms are consequently seen as being the major sources of technological change in the pharmaceutical industry whereas large firms seem to use patents strategically to retain sales.

The remainder of the paper is organized as follows: Section 2 quickly describes the relevant literature then lays out the basis for the use of patent citations and their advantages for such an analysis. Section 3 presents the methodology, the variables and the data employed, Section 4 presents the results and their interpretation and Section 5 concludes.

2 Background

In many empirical works the manufacturing industry exhibits a decreasing R&D productivity which is particularly accentuated in pharmaceuticals.¹⁰ The pharmaceutical industry is one of the most intensive knowledge sectors, devoting currently more than 20 % of sales to research and development (PhRMA, 2000). The decline of innovation is such that the average cost to develop New Chemical Entities (NCE) has risen from \$180 million in the eighties up to more

⁹Even if original data cover 1975-95 we focus on the period 1975-91 for two reasons. Firstly to deal with the truncation problem related to forward citation lags (see section "Data and Methodology" and for details Hall et *al.* 2001). Secondly to avoid bias the wave of mergers and acquisitions in the mid 90's (seen as an external acquisition of knowledge) may induce when analyzing firms' innovation efforts.

¹⁰As shown by Dimasi (1991) and Dimasi *et al.* (1999), pharmaceutical innovation costs have dramatically increased since the last decade in part due to the stricter rules on clinical trials, in addition to increasing complexities in technology discovery; see also Henderson & Cockburn (1998) and Cockburn (2006).

than \$800 millions in 2000.¹¹ The regulatory framework may have contributed to some extent to rising costs which leads to the decline of R&D productivity and an increasing difficulty to bring innovation onto the market. In addition the competition exerted by generics is stronger and stronger (Grabowski and Vernon, 1990) such that in the eighties they represent half of the prescriptions on the US market. Furthermore as it takes on average 14 years from laboratory and animal studies to FDA (Food and Drug Administration) approval (Viscusi et al. 2000), approvals in 2000 are related to patents which has been granted between 1985 and 1990. Technological exhaustion (within a dynamics of "creative accumulation") in pharmaceuticals may also explain such a decline. The emergence of biotechnologies and genomics in the eighties, redefined invention methods for drugs from randomly screening of a large number of potentially useful compounds towards a more systematic approach called "rational drug design". This revolution in the research methods has therefore induced new challenges to the extent that the NCE are more and more specific. Analogously, the role played by competitive entrants in comparison to dominant firms can shed light on the articulation between "creative destruction" and "creative accumulation" in the discovering of new compounds.

The pharmaceutical industry is also recognized as the sector where the patent is the more effective and, consequently, the principal industry relying on patents to appropriate returns to R&D and to exclude technological followers. According to Bruce Lehman (2003)¹³, President of the International Intellectual Property Institute, "the pharmaceutical industry is one of three technology-based industries in which the patent virtually equals the product. The others are the chemical industry (including agricultural chemicals) and the biotechnology industry". Levin et al. (1984) showed that a patent is the most effective to appropriate returns in industries with chemical-based technologies, such as pharmaceuticals, which makes it a very convenient field for analyses which proxy innovation activity with patent grants. However firms may also be strategically granted many "poor" patents—as many legal right to exclude—to build barriers to entry (foreclosure) or to develop existing inventions in response to increasing difficulties to innovate. To extend market exclusivity on

¹¹Source: Tufts Center for the Study of Drug Development (2001).

¹²This involves exploiting knowledge about the biochemical mechanisms causing a disease to identify or develop chemicals that inhibit such mechanisms, see Malerba & Orsenigp (2001, 2002) and Adam (2005) for a detailed description of this transition.

¹³ "The Pharmaceutical Industry and the Patent System" Columbia University Working Paper, 2003.

blockbuster drugs (those exceeding US\$ 1 billion of yearly sales) beyond patent expiration, firms use a number of strategies in response to the increasing competition of generics, allowed by policies like the *Hatch-Waxman Act* (1984), and to the threat of technological exhaustion. Nevertheless, as suggested by Caballero & Jaffe (1993) and Lichtenberg (1998), the pharmaceutical industry remains the sector with the highest rate of creative destruction at the product level. Despite the fact that less and less pioneering inventions are discovered, leading to an erosion of the number of new (technologically) promising compounds invented, pharmaceuticals remains the most research intensive sector (Achilladelis & Orsenigo, 2001; Malerba & Orsenigo, 2001; 2002).

Finally, as pointed out by Griliches (1990), the technological value across patents –within a firm's patent portfolio and across firms– largely differs. That explains partly why some studies are based on innovation surveys –rather than on patent data– to analyze firms' innovation activity. Innovations surveys present however also some drawbacks inherent to their qualitative approaches. Notably the definition of innovation, as well as the distinction of its nature (radical or not), remains subjective and presumably arbitrary heterogeneous. To deal with both of these issues we thus choose to use patent and patent citations data to assess the firms' innovation activity.

2.1 Persistence of Innovation in the Literature

A large strand of literature focuses on the persistence with which firms innovate. This literature investigates whether firms innovate persistently or discontinuously over time and attempts to assess the extent to which innovation flows within firms are interdependent over time. Contrasting views are put into light and often underline the role played by financial resources and/or technological leadership resulting from past innovation. These are either seen as an advantage to innovate or as a dead weight which limits future innovative ambitions. We can summarize that the literature analyzing patterns of innovation agrees on innovative persistence being rather strong among large innovators and that consequently few –persistent– innovators account for the large majority of patenting with quite stable ranking. In other words, these studies confirm the theoretical predictions on persistence only for a restricted group of firms.

In Nelson & Winter (1982) "success breeds success" such that past innovations that meet

commercial success are a necessary condition to finance R&D and by consequence to innovate persistently. Analogously, Simons (1995) explains that successful innovations offer technological advantages to innovate thereafter. Thus the cumulative nature of knowledge would induce state dependence in invention flows and consequently persistence in innovation. Considering competition, Arrow (1962) shows that competitive markets generate greater incentives to invest in innovation than concentrated ones. In the case of free entry, Gilbert & Newberry (1982) show that market dominant firms will preempt potential entrant investment in innovation which leads to persistence in innovation activities. Reinganum (1983) however reinstates Arrow's results by considering the case of uncertain innovations. She shows that a monopolist will seek to avoid overlapping in its product innovation portfolio, and thus will have less incentive to innovate than a competitive entrant. From another point of view, Sutton (1991) considers the sunk costs in R&D investments as an important feature to take into account in studying persistence since they build barriers to entry and create engagements to continue innovation.

At the empirical level, studies focus on the "creative destruction" and "creative accumulation" in the technological dynamics (which of the two effects prevails according to competitive circumstances and firms' characteristics). They point out the differences between dominant firms and competitive entrants in the emergence of new technologies, their improvement and consequently the innovative interactions at work in the technological path design. Schumpeter initiated many debates directing researchers towards the questions dealing with the sources of the technological change but the interaction of market dominance and past innovative activity remains still inconclusive. Several cross-sector studies demonstrate an apparent continuity, or persistence, in the firms' innovative behaviors and, in general, agreed on the fact that only a few innovators account for a large share of innovations and do it continuously (i.e. persistence in innovation is weak as a whole as only a restricted group of firms is concerned). Nevertheless, in almost all cases, the simple patent count, or the R&D activity, is used to proxy the firms' innovative behavior excepting Duguet & Monjon (2004), Peters (2005) and Raymond et al. (2005) who use innovation surveys to overcome the limitations of patent data.

¹⁴See also Aghion et al. (2002) who find an inverted U relationship between innovation and competition.

Crépon & Duguet (1997) use a panel of R&D performers and patent data to measure innovation in France. They estimate a dynamic count data model that estimates the relationship between the current number of patents to both the previous year number of patent and the amount invested in R&D. They find a rather strong persistence in innovation among formal R&D performers. Marbela & Orsenigo (1999) examine the patterns of innovative entry, exit and survival, using European Patent Office (EPO) data for six European countries through a descriptive analysis. They measure persistence by analyzing the duration of patenting after entry. They found a high degree of turbulence such as the process of entry and exit seems to support wide changes over the time in the innovators' population. Hence, a large fraction of new innovators is composed by occasional innovators even if they constitute a significant part of the whole population of innovators, despite a lower share in the total number of patents granted.¹⁵ Cefis & Orsenigo (2001) confirm the weakness of persistence in innovation in a comparative analysis of six European countries over the period 1978-93, using a Transition Probability Matrix approach and a Markov chain that distinguishes "great-innovator" and "non-innovators". They assess the probability of remaining in the same stage of patenting and found a strong persistence in the firms' innovative activity. Firms have thus a high probability of staying in their original state, persistent innovators being the principal source of technological change. In addition they find a strong heterogeneity across firms' industry and size. Similar results are found by Cefis (2003) who uses the same methodology for the UK over the period 1978-91 since she finds "little persistence in general, but strong persistence among 'great' innovators that account for a large proportion of patents requested: innovative activities, at least which are captured by patents, are persistent". 16 Geroski et al. (1997), in a duration analysis (Duration Dependence Weibull Model) that assesses the "patent spells" in UK over the period 1969-88, find little evidence of persistence at the firm level, even if persistent innovators account, once again, for a large share of the total patenting. They find similar results

¹⁵On this point Duguet & Monjon (2002) explain that in some activities, few innovators patent their inventions (see also Cohen *et al.* (1997), Duguet & Kabla (1998)). Consequently the weak persistence would reflect in fact the weak use of patents in some sectors. In addition patent data would show the persistence of "anteriority" rather than that one of innovation. However in the specific case of the pharmaceutical industry these assumptions do not hold.

¹⁶In an earlier version, Cefis (1996) already found a weak persistence in general but a strong persistence among the greatest and the smallest innovator. By distinguishing firms according to their size and sector, she sheds light on a substantial heterogeneity in the degree of persistence among the firms of the sample.

¹⁷i.e. they define the degree of innovation persistence of a firm as the number of consecutive years during which it has a recorded innovative output.

when considering "major innovations" instead of patent count. Cabagnols (2005) uses the same data to examine the impact of past patenting—the technological accumulation—on the firms ability to be persistent in innovation and finds also a positive and significant relationship.

Concerning the technological specificity of the innovation's patterns, Marbela & Orsenigo (1996) show that the patterns differ systematically across technological classes (referring to Schumpeter Mark I and II), but are remarkably similar across countries for each technological class suggesting there is no country specific effect contrarily to sectors. As a result they found that the process of "creative accumulation" is specific to the electronic and chemical industries whereas the mechanical technologies are closer to a process of "creative destruction". This seems to support the assumption that industries where innovations are primarily based on knowledge (as pharmaceuticals) are more subject to technological accumulation (v.s. pioneering innovation) than others. Thereafter, Marbella et al. (1997) wonder if persistence and heterogeneity are associated with a high degree of concentration in the innovative activity and a stability in the ranking of innovators, or whether they are associated to other variables like the firms' size and industrial concentration. As results, contrary to the Schumpeterian hypothesis, they found that the market structure doesn't play a clear role in the emergence of innovation while persistence and asymmetry seem to be the fundamental determining causes for it.

More recently, Duguet & Monjon (2004) propose to examine if innovation is persistent at the firm level by comparing propensity score and regression methods. They use several innovation surveys on French firms' innovative activity for the period 1986-1996. These data sets give information about the implementation of innovation at the firm level, without any reference to their commercial success or their patenting status. Their results indicate that innovation persistence is strong (a firm that already innovated in the past has a stronger probability to innovate in the future). In addition, the origin of the persistence depends on the size of the firm: the learning-by-doing hypothesis (dynamic increasing returns) seems to play a major role in the small sized firms whereas its weight decreases with the firms' size. Finally the study shows that the importance of dynamic

 $^{^{18}}$ Nelson & Winter (1982) define the Schumpeterian hypothesis as the fact that "A market structure involving large firms

with a considerable degree of market power is the price that society must pay for rapid technological adavance".

increasing returns should decrease with the formalization of R&D activities. The paper suggests that omitting the dynamic increasing returns leads to underestimating the innovation persistence, especially in small-sized firms. In this vein, Raymond et al. (2005) analyze the extent to which the production of innovations is subject to "dynamic economies of scale", or whether "success breeds success". They study the dynamic of innovative achievement and innovation profits in the Dutch Community Innovation Survey by estimating a dynamic probit model and find a strong persistence of innovation profits among the multi-period innovators. Recently, Peters (2005) uses data from the Mannheim Innovation Panel (manufacturing and service sectors) over the period 1994-2002 through a dynamic random effects discrete choice model. She finds that innovative behaviors are "permanent at the firm-level to a very large extent" and that skilled employees and unobservable individual heterogeneity play an important role in explaining this behavior.

Given this state of the art on persistence in innovation, an interesting addition to the literature would be to look at the nature of these inventions (technological scope, newness...) from a quantitative point of view and the different behaviors that might emerge following the firms' characteristics. In this vein, Lerner (1997) examined whether strategic behavior can be identified in the decision to introduce new products in a high technology industry: the disk drive sector. Consistently with models rising doubts about the persistence of monopoly, he found that greater innovative activity is shown by the firms which follow the leader. This result supports the idea that a second mover advantage exists in technological races Such an assumption may be tested in a dynamic approach of innovative activity. Empirical works which study persistence by distinguishing innovation "qualities" or "scope" are very scarce. Such a dimension seems however fundamental to take into account, especially in the pharmaceutical industry where the "quality" i.e. the technological magnitude—of new product is often seen as weak. In Geroski et al. (1997), an effort was made in this sense by taking into account the simple counting of patents and the number "major innovations" made at the firm level, i.e. those being technically innovative and commercially successful. However, this criteria may be questionable to the extent that the commercial success should be carefully interpreted and thus may be related to the brand-name or even the firm's advertising among other (unobservable) parameters. Since this definition involves a commercial success, the firms considered as innovative are likely to be innovation leaders or commercial leaders. Our study suggests several patent quality measures, exclusively based on forward and backward patents' citations. These quality measures only refer to the innovations' importance in a technological sense and thus allow to proxy for firms' innovation activity in a sharper way than the simple patent count.

2.2 Distinguishing Innovations Quality

Patent count, as a proxy for the firms' innovative activity, generally leads observers to assume a perfect homogeneity of quality between and within patent portfolios. Distinguishing the importance of inventions would however permit to identify the *real* sources of technological change in the industry. Taking into account the dynamic effects in such a question could offer valuable insights on the relationships existing among the persistence in innovating, the nature of the firm's R&D output and the inventors' characteristics (size, market dominance, R&D intensity, etc).

To describe how cumulative innovations are made, and consequently to understand the innovations' technological magnitude, we suggest several patent citations-based measures. The main idea supporting this methodology (widely recognized in the literature)¹⁹ is that the simple observation of firms' patenting activity is an unsatisfactory measure of the real innovative effort. This is in particular the case when firms patent intensively, regardless of the innovations' quality, following a defence and/or blocking-entry strategy as shown in Lanjouw (1998) and Lanjouw et al. (1998).²⁰ More generally, firms may also differ in terms of competence in innovating (depending on history and on other factors like the position on the supply chain), some of them being more specialized in fundamental research than others and consequently generate more technological spillovers. In the next section we also present some of the strategic use of patents that may explain differences in quality patenting. Overall, the simple patent count should therefore be interpreted carefully. Whereas technological breakthroughs are able to impel the technological change, others just deepen into an already existing knowledge. Thus some innovations may have a greater impact on technological change than others because they may provoke new technological perspectives. According

¹⁹See Scherer, 1967, Pakes & Griliches, 1980 and Griliches, 1990 among others on this point.

²⁰ As shown by previous studies, there are important differences in R&D performance across industries and firms, and the way firms rely on patents to appropriate sales; see Scherer (1967), Griliches (1990), Levin *et al.* (1987), Cohen & Levin (1989), Arundel & Kabla (1998).

to this, the main findings of the literature dealing with the firms' innovative behaviors may be contrasted, particularly concerning the persistence in innovating over the time. Hence, by distinguishing the nature of innovations, this paper shows that persistence differs widely according to innovation quality, pioneering discoveries following a "one shot" process in the short run (even if they are presumably generated by the same firms) whereas other innovations are more persistent from one year to the next.

Up to now, some authors have attempted to estimate the private value of patents through their renewal patterns or by evaluating the stock-market value generated by patents announcements, among other techniques. Pakes & Schankerman (1984) and Schankerman & Pakes (1986) have proposed to proxy quality of patents by building the value of patent rights and their distribution value for the UK, France and Germany during the post-1950 period using renewal patent data²¹. Guellec & Pottelsbergue (2000) study patents' values by evaluating the probability of obtaining a patent grant at the European Patent Office in function of the technological value of innovation, patenting and innovation strategies (collaboration etc.) followed by applicants at the international scale.

Trajtenberg (1990) is the first to construct an indicator of the value of innovation by weighting patent grants with the citations they received. He finds a close association between citation-based patent indices and independent measures of the social value of innovation in the field of a particular innovation. An interesting methodology to build a quality-innovation index has been proposed by Lanjouw & Schankerman (1999). Using information on individual patents (the number of claims, the forward and backward citations and the family size) to build composite index of quality, they find in particular, that the patent quality index shows significant power in predicting which patents will be renewed and which will be litigated. Further, Lanjouw & Schankerman (2004) show that research productivity is negatively correlated with the patent quality index whereas it is positively correlated with the stock market valuation of patented innovations. Through an empirical investigation concerning 100 US manufacturing firms, the authors show that the use of

²¹They show that the variation in the quantity of patents in different cohorts tended to be negatively related to the variation in their mean values. As the authors pointed out, this finding implies that exclusive reliance on patent counts for measuring secular trends in the value of patented output could be quite misleading.

this quality adjusted measure of innovation could explain the so-called $R\mbox{\ensuremath{\mathcal{C}D}}\ paradox$: the apparent decline in research productivity in the decade 1980-89.²² As they argue, it is likely that firms face a trade off between "quality" (i.e. importance or scope) and "quantity" of innovation such as one should expected a negative relationship between patent counts and the average patents' quality at the firm level, conditional on R&D. Such a result, as the authors indicate, would generate a different relationship between R&D and simple patent counts as compared to R&D and quality-adjusted patents.

2.3 The Strategic Dimension of Patents

An important aspect of patents may be their potential strategic dimension. Hall & Ziedonis (2001) examine the "patent paradox" i.e. the fact that firms do not rely to patents to appropriate return of R&D more in the 1980s than before despite an unprecedented surge in patenting, they show that the "1980s strengthening of U.S. patent rights spawned a 'patent portfolio race' among capital-intensive firms". They consequently underlined the use of patents as a strategic variable to build legal rights to exclude competition in the semiconductor industry. In the study based on a survey questionnaire by Cohen et al. (2000), firms seem to rely on a large range of mechanisms to protect the profit due to innovation. They found patents tend to be the least emphasized whereas secrecy and lead time seems to be the most used strategies in the majority of the manufacturing industries. In the specific case of the pharmaceutical industry however, firms may more rely on patents as strategic variable to preserve their business from competition than in other sectors.²³ The main reasons supporting this opinion stand on the fact that secrecy is an extremely weak instrument of protection because of the (publicly available) clinical trials required in the development of each drugs and also because the pharmaceutical firms' outcomes are closely linked with the life of princeps' patents. As a consequence, to extend market exclusivity on drugs beyond patent expiration, a number of strategies are implemented to deter entry in order to preserve monopoly power. Among them, Carlton & Gertner (2002) show that "the combination of dynamics, uncertainty, and market power

²²Hence Lanjouw & Schankerman (1999, 2004) consider that if innovation varies widely in value, a part of heterogeneity is due to innovation at birth. As a result they show how it is possible to foresee the "value" of an innovation via the four indicators mentioned above. The composite indicator contains the number of forward and backward citations, the claims and the family size of each patent and is estimated as one-factor latent variable model where the conditional mean is a linear combination of the indicators.

²³See Scherer et al. (1959), Mansfield et al. (1981), Mansfield (1986) and Levin et al. (1987).

leads to one of the most important features of many R&D-intensive industries an important form of competition is in R&D to replace the existing technology winner that has static market power with another based on improved technology". Hence, patenting around existing chemical entities ("me too drugs", ever-green patenting, etc.) have indeed become an important strategy followed by pharmaceutical firms.²⁴ The increasing threat of generics, allowed by policies like the Hatch-Waxman Act (1984), may consequently motive research intensive firms to use patents as a strategic variable to maintain their revenue. Such strategy imply evergreening that occurs when a brand-name manufacturer "stockpiles" patent protection by obtaining separate patents on multiple attributes of a single product.²⁵ To evergreen their products, Carlton & Gertner (2002) explain that the originator company will develop a "life-cycle management plan" composed not only of patent strategies, but an entire range of practices aimed at limiting or delaying the entry of a generic product into the market. Some of the evergreening strategies are line extensions and so-called next-generation drugs.²⁶ Patenting around existing chemical entities seems however to be more and more sought by pharmaceutical firms as shown by Lichtenberg (1996). Much of sequential innovation thus results from internally generated research and sequential product innovation which constitute an important feature of the pharmaceutical industry. Hence 60% of the new drugs approved in the 1990s were for "new formulations" or "new combinations" of already approved compounds. According to the Pharmaceutical Research and Manufacturers of America (PhRMA) industry data indicate that of the \$26 billion spent by U.S. firms on pharmaceutical research in 2000, \$5 billion (19 %) was spent on post-launch R&D for new indications, new formulations, and other improvements to existing products. Sequential product innovation is spurred by and fosters competitive pressures." These market developments, carefully balanced with protections for seminal intellectual property, have spurred additional innovation and competition. Hence, brandname manufacturers introduce new dosage formulations that provide, a priori, superior therapeutic properties than the original formulation, and introduce over-the-counter versions of products. In

²⁴See Lichtenberg (2000, 2001).

²⁵These patents can cover everything from aspects of the manufacturing process to tablet color, or even a chemical produced by the body when the drug is ingested and metabolized by the patient (see European Generic Medecines Association: www.egagenerics.com).

²⁶Some of the evergreening strategies are also switching from prescription-only to over-the-counter status, exclusive partnerships with chosen generics manufacturers, direct-to-consumer advertising, defensive pricing strategies or even more to establish a subsidiary generics unit to compete in the generics market before independent generics companies are allowed to do so.

parallel, breakthrough drugs may also face competition within their initial patent life from other branded drugs of the same therapeutic class.²⁷ Consequently, the research intensive firms tend to rely heavily on product differentiation to achieve competitive advantage over other branded rivals what, to a certain extent, can be considered as one strategic use of patent. Further, with the increasing generic competition allowed by the Hatch-Waxman Act, branded manufacturers tend to develop improved products to retain sales which can be another strategic use of patent.²⁸

Strategic patenting to enclose sub-markets in order to face competition from other research intensive firms (i.e. brand name manufacturers) or production intensive firms (i.e. generics producers), may influence the technological change by extending, to some firms, the legal right to exclude imitators up to a foreclosure possibility on a whole technology. Statistically, the strategic dimension of patents may bias the observation of firms' innovative efforts based on patents data. Indeed, it remains difficult to distinguish strategic patenting from creative accumulation since in both cases patents are granted. Nonetheless the differentiating of patent values in a technological sense allows to identify true innovations from strategic ones.

3 Data and Methodology

This study pursues several research goals. First, an analysis at the patent level is conducted in order to make a distinction of Leader and Follower (or pioneer and incremental) patents, on one hand, and to distinguish patents in term of technological value on the other hand. These distinctions are made thanks to the number of citations made and/or received per patent. Second, an exploration of the pharmaceutical firms' persistence to innovate, conditional on the different kind of innovations' stocks, is presented. Third, the feedback effect –the dynamics showing the persistence of innovation over the time– of the different patent grants is explored through an innovation function equation.

We use two data sources. Firstly, we extracted patent data from the NBER patent data file, by Hall et al. (2001) concerning USPTO (United States Patent and Trademark Office) utility patents

²⁷See the "between patent competition" in Lichtenberg & Philipson (2002).

²⁸A recent example is that one of *Mopral*, which has recently lost its patent protection, which carried out AstraZeneca to launch *Inexium*, an improved version, simultaneously with the entry of its generics.

granted in the classes 424 and 514 (*Drug, Bio-Affecting and Body Treating Compositions*) over the period 1973-1999. Secondly, we gathered firms' patent data and match it by using the firms' CUSIP (*Committee on Uniform Security Identification Procedure*) identifier code with individual economic data from Standard & Poor's COMPUSTAT annual industrial files database that covers the period 1975-1995.²⁹ Data are thus reduced to a sample of 77 pharmaceutical firms patenting at the USPTO between January 1975 and December 1994. We build firms' quality-adjusted portfolio of patents as the sum of total patents weighted by their citation index which is also provided by the NBER.

Micro-Level Data from COMPUSTAT concerns R&D spending, capital stock, number of employees, net sales, capital expenditures, cash flow, and operating income (constant thousand US\$ 94). After merging the two data sources and keeping only firms having been granted patents at least three times consecutively at USPTO, we end up with a rather small sample of 77 pharmaceutical firms in a unbalanced panel data covering the period 1975-95. Contrary to other studies, we consider only firms who patent regularly. By this focus we want to consider innovative behaviors among real inventors: in the pharmaceutical industry only few patents become drugs³⁰ and laboratories must test hundreds of patented molecules before obtaining a result which will has a chance to be claimed an authorized drug. This relatively reduced sample eliminates the bias that may exist when considering also firms that rarely patent. True drugs inventors have to test many new chemical entities (NCE) and consequently have to be granted many patents before obtaining a new promising compound to commercialize.

The database contains approximately 10,000 patents referred at USPTO. In this study, we focus on the innovations that concern exclusively NCE and we do not take into account other products. This choice is motivated by the fact that the NCE represent the most important share of the R&D effort made by firms and because strategic behaviors are expected on this market segment. The remaining patenting (excluding drugs) is assumed to represent a noisy measure of the real

²⁹Matching between two sources has been made through an intermediary file the containing CUSIP code (Hall *et al.* (2001)) and the corresponding corporate company name and USPTO's assignee code. Since Compustat includes firms that are traded in the US stock market (manufacturing firms) our final database concerns mainly American Pharmaceutical Firms.

³⁰It is well known that in the pharmaceutical industry very few of patents granted will become commercialized drugs and the failures during the clinical trials are enormous (see works of Grabowski).

innovative effort made by firms and a weak share of their revenue. This paper deals therefore exclusively with pharmaceutical firms who extract their revenues from the commercialization of drugs because it is assumed to be the core of innovative activity in pharmaceuticals. We build firms' total patents portfolio weighted by their citation intensities, in addition to the explaining variable of total patents counts. Stocks of R&D, non-weighted and weighted patents are built following the perpetual inventory method using a 15% depreciation/obsolescence rate as traditionally used in the literature.³¹

We address the problem of truncation related to patents and citations by implementing the methodology proposed by Hall et al. (2001). There is an important lag between patent applications and patent grants (in average about two years) so we observe only a small fraction of the patents applied which eventually will be granted as we approach the last year of patent data. Patent counts should then be corrected using weighting factors according to the estimated applicationgrant empirical distribution (ibid).³² Similarly, to deal with the problem of truncated citations, Hall et al. (2001) propose to estimate the shape of the citation-lag distribution, i.e. the fraction of lifetime citations (defined as the 30 years after the grant date) that are received in each year after the patent grant. Accordingly, the total citations for any patent (for which we observe a portion of its citation life) is estimated by dividing the observed citations by the fraction of the population distribution that lies in the time interval for which citations are observed. It is assumed that this distribution is stationary and independent of overall citation intensity. Although the normalization of citations reduces the striking contracting tendency at the end of the period, it does not eliminate the problem completely. Because our empirical study focuses on the period 1975-1991, it minimizes such a bias. The main reason of the shortening of our panel to 1975-1991 is however that it limits the problems inherent to the wave of mergers and acquisition (M&A) that characterized the pharmaceutical industry in the mid-nineties. This restructuring of the sector is indeed assumed to introduce a bias in the observation of innovative activities -at the firm levelsince the acquisition of knowledge cannot be taken into account.

³¹See Griliches (1989), Hall & Mairesse (1995).

³²We use patent data from 1975, patent stocks are built for those firms patenting before this year. Therefore we do not need to adjust the patent counts for application lags but we will have to adjust the patent counts for the last periods. Patent counts beyond 1993 (since only about half the patents applied for in 1994 are observed due to grand lags).

3.1 Distinguishing Innovations from Patents and Citations

Originality Index

In order to distinguish patents in terms of technological specificity, we use a citation-based measure suggested in Henderson, Jaffe and Trajtenberg (1998) and Hall et al. (2002). Innovation Originality captures the extent to which a patent cites a wide range of technological classes or if its technological basis is rather concentrated on few technological areas. The measure of Originality is a Herfindahl concentration index such as:

$$Originality = 1 - \sum_{k=1}^{N_i} \left(\frac{Ncited_{i,k}}{Ncited_i} \right)^2$$
 (1)

where k is the index of patent classes and N_i is the number of different classes to which the cited patents belong.

Hence if a new patent cites patents that belong to a narrow set of technologies (UPSTO patent classes), the originality score will be low, whereas if it cites patents in a wide range of fields would render a high score (notice that $0 \le Originality \le 1$ and that higher values represent less concentration and hence more Originality). It thus measures how the innovator's R&D is diversified or specialized. As shown by Cockburn & Henderson (1998) and Henderson & Cockburn (1996), pharmaceutical firms which are more technologically diversified have been found to enjoy a stronger R&D productivity thanks to economies of scope.

3.1.1 Citations Adjusted Patents

As a measure of innovations' technological "quality" or significance, we weight the firms' yearly patent count by the number of forward citations it generates the following years.³³ Such a measure exhibits the impact a patent portfolio, and consequently a firm in a given year, will exerts on the technological dynamics. Indeed, the number of citations received show the level of influence that an innovation exerts on further innovations and consequently its technological importance. The

³³It is important to note that the complete listing of backward citations is made by the patent examiners and not only by the patentor itself: there is consequently no potential bias due to the firms' claims.

variable Citations Adjusted Patent (CA) shows the (yearly average)³⁴ number of citations received per the patents of the firm which are granted this year. It represents one of our proxy for the firms' innovative activity. Such a variable increases with the number of forward citations and decreases with the number of patents granted this year by the firms. As a consequence, the larger the number of citations a patent portfolio has received, the greater its "quality" or "influence". However such a measure take into account only one dimension of innovation, the technological impact, and does not consider its cumulative aspect. To track the pioneering behavior this measure is consequently not completely satisfactory insofar as it does not refer to the citations made (which can proxy for the degree of novelty) but only on the citations received (which proxy for the technological importance).

Leader and Follower Patents

We consider a patent represents a pioneering discovery if it satisfies two criteria: first the innovation must be non cumulative, second it must be technologically influent. As a consequence a pioneering innovation must be both new and influent. Hence we separate patents in two categories which denote both their technological novelty and their importance. Compared with the simple patent weighting by citations received, this patent distinction considers both forward and backward citations. A patent is Leader if its forward citations exceeds the yearly industry median³⁵ whereas its backward citations remains inferior to the yearly industry median (considering the citations yearly observed in the patent classes 424 and 514). As a consequence a Leader patent is defined relatively to the other patents granted the same year (see Figure 3 in annex).

Such patents exhibit, in comparison to the median, of a greater influence on the technological path design **and** of a lower dependence on existing technologies. *Leader* patents are consequently those which, technologically, lead the technological change, thanks to a relatively strong creativity

 $^{^{34}}$ Because our data are yearly aggregated at the firms level, the weighted patent count is represented by the ratio of yearly citations received by the number of patents granted.

³⁵It would be possible to use the mean instead of the median since there is no sensible differences between the two type of calculations. Results do not change according to the type of calculation used.

³⁶Forward and backward citations included in this mark cover the period 1963-2000; as a consequence we consider all citations received up to 2000 whatever the granting date. As our study only cover the period 1975-91, patents granted in 1991 can receive citation up to year 2000. In addition, as mentioned previously, recall patent citations used in all the study have been normalized following the methodology proposed by Hall *et al.* (2001).

which is widely diffused in the industry. Follower patents as the remaining patents of the sample so that they represent all patents which are not considered as pioneers ($Leader+Follower=Total\ of\ patents$). Follower patents are those which have received at most as many citations as the yearly industry median and which have made at least as many citations as the yearly industry median (see extension for the results of estimations on Follower patenting which are not presented here). To our knowledge, there is no empirical works have differentiated the inventions like this. Duguet (2002), for example, distinguishes incremental and radical innovations on the basis of the firms' claims in a innovation survey which do not constitute an homogeneous technological viewpoint.

For the full period (before having shortened the panel to 1975-91) we have the following trends in the granting of *Leader* and *Follower* patents:

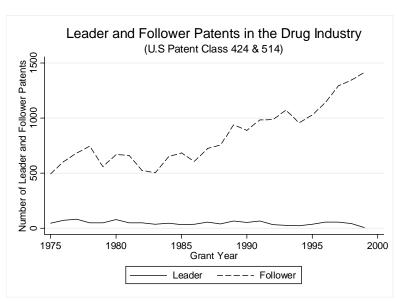


Figure 1

Source: own calculations from NBER Patent Data File

The number of Follower patents apparently increases over the time whereas the number of Leader patents granted shows a slower and contracting movement along the period. The propensity to grant pioneering discoveries decreases over the time, especially since the mid eighties (the Hatch Waxman Act was enacted in 1984). The ratio of these two indicators (see appendix) confirms

a relative decline in the *Leader* patenting compared to the *Follower* patenting. In fact, fewer and fewer patents propose radical technological change which assumes improvement strategies characterize the period considered probably as a response to the new competition impulsed by biotech firms. It could imply a greater use of internal knowledge if firms seek to stand on their previous inventions to introduce new products. Yet firms can also improve technologies that are not their own discoveries.

Internalized Spillovers

When a patent stands on the patented firm's previous innovations, it indicates a process of internalized spillover that can be evaluated through the number of self-citations that are made (the extent to which a patent cites the previous patents granted by the firm).³⁷ According to Hall & al. (2001) an interesting issue is that "presumably citations to patents that belong to the same assignee represent transfers of knowledge that are mostly internalized, whereas citations to patents of 'others' are closer to the pure notion of (diffused) spillovers." In other words, few citations to rival firms, or others entities, would mean that the firm does not rely on external spillovers as much as it relies on internal knowledge. The figure in the appendix shows that the use of self citations increases dramatically over the period. Hence the firms of our sample apparently rely more and more on their previous inventions to innovate. Such a trend highlights the increasing difficulties to innovate radically over the time i.e. to create new knowledge. Empirically these observations coincide with the introduction of the $Hatch-Waxman\ Act$ (enacted in 1984)³⁸ which provides incentives to support the development of generic versions of off-patent drugs and permit patent owners to recover time lost during FDA approval. As shown by the figures 1 and 2, it is possible to hypothesize that the pharmaceutical firms seek to retain their sales through product development strategies in order to face the pressure exerted by generics. More generally our

³⁷The percentage of self-citations is computed as in Hall *et al.* (2001): for each patent that has an assignee code we count the number of citations that it made to (previous) patents that have the same assignee code, and we divide the count by the total number of citations that it made.

 $^{^{38}}$ Since the law's passage, the generic industry's share of the prescription drug market has jumped from less than 20 % to almost 50 % today. The economic realities of non-innovator commodity production allow generics to enter the market at a significant discount, and for prices to decrease with increased generic entry. Before the 1984 law, it took 3-5 years for a generic copy to enter the market after the expiration of an innovator's patent. Today, generic copies often come to market as soon as the patent on an innovator product expires. Prior to the Hatch-Waxman Act, only 35 percent of top-selling innovator medicines had generic competition after their patents expired. Today, almost all innovator medicines face such competition (see PhrMA (2002)).

data confirm previous empirical findings relating a decrease of inventiveness in pharmaceuticals: fewer and fewer pioneering inventions are discovered leading to an erosion of the number of new (technological) promising compounds invented.

In the pharmaceutical industry our proxies of innovation based on citations criteria (*Leader*, *Follower*, *Citations Adjusted* patenting) allow us to measure the propensity to improve already existing solution rather than to create technological breakthroughs. They are thus means to put into evidence the kind of strategy of research led by the current pharmaceutical firms and how the past innovative activity of these firms may influence their present innovative behaviors. Several patent stocks are therefore built for further employment in the knowledge production functions for each firm.

3.2 An Innovation Equation

Propensity to Innovate: Distinguishing the Nature of Innovations

A key focus of interest in this paper is the estimation of an innovation equation I_{it} where I denotes either the Non Adjusted patent count, the Citations Adjusted patent count or the Leader patent count which are described above. Following Hausman et al. (1984) and Blundell et al. (1999), for a latent variable of innovation I_{it} , we consider the knowledge production function:³⁹

$$I_{it} = f(x_{it}, \eta_i) \tag{2}$$

where x_{it} is a vector of firm i characteristics (e.g. past R&D investments) and unobservable invariant firm-specific factors are represented by the term η_i . It represents permanent unobservable differences across firms affecting the production of innovation firms (appropriability conditions, marketing strategy or financial characteristics). This relationship is derived as the outcome of a firm's optimal search rule for innovation (Blundell *et al.* (1995), Reinganum, 1989) where the search process is assumed to generate innovations in future periods. I_{it} represents the several patent-based proxies for innovations made by the firm i at time t described previously. Because

 $^{^{39}}$ See also Hausman et al. (1984); Winkelmann & Wimmermann (1992); Crepon & Duguet, (1997); Blundell et al. (2000), among others.

the number of patents is a non-negative integer, we adopt count data regressions as described by Hausman *et al.* (1984) and Blundell *et al.* (1999). We model the conditional mean as a multiplicative or log link function of explanatory factors as:

$$I_{it} = \exp(x'_{it}\beta + \eta_i) + \varepsilon_{it}$$

$$= \mu_{it}v_i + \varepsilon_{it}, \quad for \ i = 1, ..., N \text{ and } t = 1, ..., T$$
(3)

where $\mu_{it} = \exp^{(x_{it}\beta)}$, $v_i = \exp(\eta_i)$ and ε is a disturbance term with expected value 0. x_{it} is a vector of observed explanatory variables, and β is the corresponding vector of parameters to be estimated including lagged values of firms' market share, R&D expenditures and stock of knowledge, etc. The full empirical model is defined as:

$$I_{it} = \exp(\beta_1 \log(Sales)_{it-1} + \beta_2 \log(R\&D)_{it-1} + \beta_3 M S_{it-1} + \beta_4 C S_{it-1} + \beta_5 Originality_{it-1} + \beta_6 Self_{it-1} + \beta_7 G I_{it-1} + \eta_i) + \varepsilon_{it}$$

$$for i = 1, ..., 77 \text{ and } t = 1, ..., T; \text{ where } I_{it} = \{NA_{it}, CA_{it}, L_{it}\}$$

$$(4)$$

In this specification, firms' innovation propensity is conditional on previous market power, measured by the lagged value of total sales $\log(Sales)_{it-1}$, R&D effort $\log(R\&D)_{it-1}$, market-share MS_{it-1} , Citations Share CS_{it-1} , Originality index Originality_{it-1} (calculated according to the fromula (1)) and internal spillover (Self-Citation propensity) $Self_{it-1}$. Considering the dynamics of innovation, we then introduce the lagged knowledge stock variables $G_{NA, CA, L; t-1}$ (where subscripts NA refer to Non Adjusted patent stock $G_{NA, t-1}$; CA to Citations Adjusted patent stock $G_{CA, t-1}$; and L to Leader patents stock $G_{L, t-1}$) into the knowledge production function (see Blundell et al. 1999 for a comparable specification). All stocks are calculated following the perpetual inventory methods proposed by Hall et al. (2005).

The expected effects of market share and total sales on innovation propensity are ambiguous. Strategic considerations imply that the marginal benefit of an innovation (an additional increment to the firm's innovation stock, $G_{i,t}$) may be more valuable to a market leader than to a follower as shown through the "efficiency effect" described in Gilbert & Newbery (1982). In contrast,

dominant firms may be more reluctant to innovate as they find it more profitable to exploit existing innovations.⁴⁰ This case thus illustrates the Reiganum's "cannibalization" model (1989) or "displacement effect". The self citations show how the firm relies on the previous inventions it made to generate NCE. On the one hand, it is expected that it influences positively on the Non Adjusted patenting because of the product development strategies described previously, and negatively for the Leader patenting if we hypothesis that self citations exhibit the cumulative nature of innovation within firms. On the other hand, the internal spillover effects may also help to generate high quality innovations because they represent a technological advantage as the firm exploits its knowledge to invent. If we hypothesis that pioneering discoveries follow a multi stage process of invention requiring several knowledge, self citations may have a positive influence. As a result of these two possible impacts, the potential effect of internalized spillover (i.e. self citations) on the firms' innovation propensity and persistence in innovating is undetermined.

Individual knowledge stock variables are obtained by accumulating past patents granted: $G_{i,t} = I_{i,t} + (1 + \delta G_{i,t-1})$. The stock of knowledge increases continuously by the addition of new patents, but it also continuously decreases at the constant depreciation/obsolescence, rate δ (15%).⁴¹ Knowledge-stocks should exert a positive effect on the propensity of the firm to innovate as there are dynamic returns in the production of innovation. Cumulated technological experience facilitates in some way current R&D productivity: R&D economies of scale (see Teece, 1980; Cohen & Levin, 1989; Chandler, 1990), learning-by-doing, and learning-by-learning effects (see Rosenberg, 1987 and Cohen & Klepper, 1996). Concerning dynamics of innovation it is expected to find higher persistence in low quality patenting for firms that use patent as a strategic variable to preserve market power, whereas highest quality (i.e. Leader) patenting should be less persistent over the time since it requires—presumably—large R&D spending and may need developments to be commercialized. Concerning the Citations Adjusted patenting the expected effect of lagged patenting is more ambiguous because it capture two dimensions: that one of the number of patent granted (—) and that one of the number of citations received (+). We also include two additional lagged

⁴⁰They may also rely on alternative strategies to keep market power as presented earlier (technological foreclusion...).

⁴¹Initial values of $G_{i,t}$ correspond to the pre-sample stock of patents for firms patenting before 1975, otherwhise patent' stocks for firms appearing after 1975 are calculated according to the perpetual inventory method following Griliches (1989) or Hall & Mairesse (1995).

terms referring to the firms' innovation degree of *Originality* and the firms' citations (received) share. They constitute the yearly mean value of firms' patent portfolio. The firms' citation share represents the share the firm own in the industry total forward citations (i.e. the sum of citations received) by patents granted in classes 424 and 514. It thus measures the degree of technological leadership. If technology-leaders have stronger incentives to remain in the innovation race, it should enter positively for the firms' innovation propensity as mentioned in Segestrom & Woniereck (1999) then Hörner (2001). Nonetheless, its impact must differ a priori according to the quality level of patenting (see Henderson, 1993).⁴²

Estimation Method for a Linear Feedback Model (LFM)

An important feature of our study is the estimation of a dynamic model (i.e. including linear feedback) to assess the persistence with which firms innovate. Given the panel dynamic specification of the model, several practical problems have to be handled: first, the autocorrelation problems imposed by the lagged variables. These lagged variables are by nature dependent on past disturbances, which makes them predetermined variables in the equation. Second, we have to deal with the time series cross-section nature of data and account for the presence and features of the unobserved components of residuals (i.e. non-observed heterogeneity). Third, the appropriate lag length of the auto regressive-distributed lag model have to be determined.

A series of strong assumptions must be respected in order to apply traditional OLS or panel data estimators. Including the lagged dependent variable as one of the regressors makes pooled OLS as well as classic error component estimators obsolete. Poisson or Negative Binomial models, because they assume that the regressors are strictly exogenous, cannot be used as mentioned by Montalvo (1997) and Blundell et al. (2000). The count panel data literature has largely focused on estimating models for patenting and the returns to R&D investments. A seminal paper of Hausman et al. (1984) initiated a growing literature estimating patent and innovation production functions using the Generalized Method of Moments (GMM) estimator allowing for correlated firm specific

⁴²Likewise, a weak citation-share indicates that other firms or competitors own a larger part of the new technology. Hence competitive spillovers may have a negative rivalry effect on a firms' likelihood to apply for a patent: the more competitors invet in R&D, the less a firm is likely to invent a new technology (see Loury (1979), Lee and Wilde (1982)).

effects and weakly exogenous inputs.⁴³ It involves estimation of a dependent variable as a function of its lagged value and other endogenous, pre-determined and exogenous variables in the presence of unobserved heterogeneity. The model is estimated in two stages using the residual of the first stage to compute an optimal weighting matrix, which is subsequently used in the second stage. As we analyze the effects of lagged innovation flows on the current propensity to innovate, we employ the nonlinear GMM method discussed and implemented by Windmeijer (2002) – ExpEnd—and used in similar conditions by Kim & Marschke (2005) then Salomon & Shaver (2005).⁴⁴

The conditional mean in the LFM is defined as:

$$E(I_{it} \mid I_{it-1}, x_{it}, v_i) = \gamma I_{it-1} + \exp(x'_{it}\beta)v_i$$

$$\equiv \gamma I_{it-1} + \mu_{it}v_i$$
(5)

We implement the Arellano and Bond test for first and second order serial autocorrelation of residuals (AR(1), AR(2)) in the differenced error terms to test the validity of the set of instruments (reported at the bottom of each table). If it is not serially correlated, the difference residuals should be characterized by negative first-order serial correlation and the absence of second-order serial correlation (which is the case for all our equations). Then, the Hansen test (–two steps– SYS-GMM) of over-identifying restrictions is applied: it tests for correlation between the instruments that are excluded from the second stage model and the residuals. It conducts a test for the null hypothesis that the remaining theoretical orthogonality restrictions are equal to zero (see Hansen, 1982 and Sargan, 1985). Failure to reject the null hypothesis indicates that the instruments are valid, and then supports the validity of the model specification (which is the case for all our equations).

⁴³See the development of the quasi-differencing approach of Chamberlain (1992) and Wooldridge (1991, 1997) by Montalvo (1997), Cinera (1997), Crépon and Duguet (1997), Blundell *et al.* (1999) and Blundell *et al.* (2002).

⁴⁴The different parameterization between the multiplicative feedback model (MFM) and the liner feedback model (LFM) (Blundell et al. (1999), Cincera (1998)) implies that, in comparison to the LFM, the coefficients $\beta E(I_{it})$ in the MFM measures the short run impact of a change in X_{it} . As explained by Blundell et al (1999), in the MFM the nonlinear dynamic makes it difficult to judge the stability properties of the model and the potentially important feedback parameter is sensitivity to large innovation counts. In a similar study, Blundell et al. (1999) implement both specifications and both models are found to yield similar estimates for the main parameters of interest. Although a non-nested comparison has suggested a preference for the LFM specificiation.

The full dynamic model is defined as:

$$I_{it} = \exp(\beta_1 I_{it-1} + \beta_2 I_{it-2} + \beta_3 I_{it-3} + \beta_4 I_{it-4} + \beta_5 \log(Sales)_{it-1} + \beta_6 \log(R \& D)_{it-1} + \beta_7 M S_{it-1} + \beta_8 C S_{it-1} + \beta_9 Originality_{it-1} + \beta_{10} Self_{it-1} + \eta_i) + \varepsilon_{it}$$

$$for \ i = 1, ..., 77 \text{ and } t = 1, ..., T; \text{ where } I_{it} = \{NA_{it}, CA_{it}, L_{it}\}$$

where I_{it-n} denote the feedbacks (I = NA, CA, L and n = 1...4) successively included in the equation.

4 Empirical Results

Table 1 presents summary statistics describing the data. Averaging across all firms and years, our sample spent on average \$283 in R&D and has average sales of \$2,786 (thousand \$US 1994) whereas the average market share (the share of the firm in the whole sector's sales reported by Compustat) is 0.5% with a rather large standard error (0.9). When looking at the innovations made by firms, expected values are found since the yearly Non Adjusted patenting is widely stronger than the Leader patenting (on average for 10 patents applied only one is a Leader). Our firms grant in average 25 patents over the period with (approximately) 3 Leader and 22 Follower patents (recall we take only account for patents granted in classes 424 & 514). On average our firms receive 6 citations per patent and the ratio of total citations received by each patent stock is almost 23 (versus a maximum of 135). Patent stocks appear very heterogeneous: 25.4 in average but 536.5 in max (recall patent stocks are continuously depreciated over the time and consequently values are not integer). This first exploration of the data thus first indicates that they are relatively few innovations made in volume compared with Non Adjusted patenting.

- Table 1 about here -

4.1 Propensity in Innovating

Table 2 displays the estimations of equation (4) on the innovation equation using the GMM-Wooldridge estimator on our different proxies for firms' innovative activity. Columns 1-2 display results of *Non Adjusted* patents, whereas columns 3-4 concern estimations of *Citations Adjusted* patents and columns 5-6 concern estimations of *Leader* patents.

- Table 2 about here -

Results indicate that the role played by internal spillover, the Self-Citations variable, is significant to explain the Citations Adjusted and especially the Non Adjusted patenting. The effect is the largest for the simple patent count and is not significant for the Leader patenting (column 1, 3 and 5) what suggests firms which often rely on their previous inventions to innovate do not grant the most cited patents. Product developments leading to low quality innovations (in a technological sense), technological improvements would tend to be less cited than others. Considering the specifications 3-4, the weak stability of this variable shows that it captures the dynamic process of innovation: the coefficient strongly decreases when introducing the patent stock (columns 1-2) and becomes negative when introducing the Citations Adjusted patent stock (columns 3-4).

Concerning the role played by market power, interesting results are found: the firms' market share is negatively correlated with the *Citations Adjusted* patenting and positively with the *Non Adjusted* patenting while it is not significant to explain the *Leader* patenting. The amount of sales of the previous period confirms that the firms' level of commercial activity (or size) is negatively correlated with the quality of inventions: the smallest firms seem indeed to be the most cited and consequently those having the largest technological influence. In addition the coefficient of the amount of sales is significant and negative to explain the *Leader* patenting confirming that influent technologies comes essentially from firms with a low commercial activity (presumably a low financial leadership). Consequently, if the firms' market power is not significant to explain the pioneering behavior, the amount of sales, as proxying for the firms size and/or level of commercial activity, seems to matter. These results then confirm the Reiganum's cannibalization model finding:

dominant firms have few incentive to provoke the technological change by fear of conflicts in their product portfolio and overlaps in their source of revenue it may cause. More generally, another explanation sheds light on some possible research intertia: largest firms have difficulties to take some distance with their own knowledge base and consequently to generate radical technological changes.

An interesting finding is the role played by the various patent stocks in the propensities to innovate.⁴⁵ Stocks are always positive and significant which suggests, as expected, that the firms' knowledge base plays positively in the propensity to innovate. Nevertheless, the patent stocks' coefficients are rather small but appears relatively strong for the *Leader* patent stock. The *Leader* patent stocks are thus strongly correlated with the current *Leader* patenting suggesting only some firms are responsible for a large share of the technological breakthroughs.

The R&D expenses are always significant and positive even if substantial differences across coefficients suggest a greater importance for the Leader patenting, then for the Citations Adjusted ones and least for the Non Adjusted patenting. As expected, the level of R&D expenses is therefore correlated with the importance of inventions: the higher the R&D expenses, the larger the probability to grant Leader patents. It is interesting to note that the simple patent count is slightly connected with the past R&D expenses, compared to the other patenting. It thus reinforces the hypothesis according to which (large) firms may have a strategic use of patents since they seems weakly linked to a real innovative effort as measured by the R&D activity. Considering the diversification of the R&D, the Originality score is always positive and a particularly large effect is found for the Leader patenting. Recall that innovations' Originality constitutes our measure of firms' R&D diversification.⁴⁶ Hence, confirming previous studies, pharmaceutical firms which are more diversified in their knowledge base (larger scope of R&D) are found to enjoy a stronger R&D productivity (due to R&D economies of scope). Surprisingly this R&D diversification is found to have the largest impact on Leader patents and the lowest on Citations Adjusted patents. The scope of R&D therefore stimulates the newness and importance of research output even if the effect is relatively low when considering only the importance of innovations disregarding newness (Citations Adjusted

 $^{^{45}}$ Stocks are calculated according to the perpetual inventory method using a yearly 15% depreciation rate.

⁴⁶See Cockburn & Henderson (1998), Henderson et al. (1998) and Henderson & Cockburn (1996).

patents). The diversification of R&D therefore appears to be an important factor contributing to pioneering discoveries. It suggests that spillover occurring between technological classes support the firms' inventiveness. To a certain extent, such an importance of *Originality* for *Leader* patenting highlights the potential importance of links (i.e. strategic interactions) between the different dimension for the pharmaceutical research (presumably biotechnologies/pharmaceutical and chemical/pharmaceutical).

Finally these estimations suggest at first sight that small firms are more influent whereas large firms appear to be mainly technological developers through a strong (Non Adjusted) patenting activity. While the Non Adjusted and Citations Adjusted patent stocks have a significant but rather small impact on the current propensity to innovate, the Leader patent stock is relatively important. This highlights the role played by small research intensive firms for the technological path design in pharmaceuticals.

4.2 Dynamic of Innovation

Tables 3, 4 and 5 display the estimations of equation (6) on the firms' persistence in innovating over the time (the dynamic model). Table 3 displays results of Non Adjusted, whereas Table 4 concerns estimations of Citations Adjusted and Table 5 shows estimations of Leader patenting. We analyze the feedback of past innovations up to four years before the current propensity to innovate as a means to characterize the firms' persistence in innovation. For each equation we assess the feedback's effect of firms' innovating activity in t-1, t-2, t-3 and t-4 on their current innovation flows. We firstly present results on Non Adjusted then on Citations Adjusted and Leader patenting. The equations assessing the persistence with which firms innovate confirm previous findings: innovations' quality is negatively correlated with the firms' level of activity (firms' dominance). In addition, the persistence in innovating is inversely proportional to the quality of patenting such that highest quality innovations are the least persistent, at least in the short run.

The role of R&D expenditures is always significant and positive regarding the different patenting propensities but its score is increasingly large according to the technological importance of innovations. Hence, as expected, the technological influence (the propensity to be cited) and the innovation novelty are linked with the firms' effort in R&D. Cohen & Kleppers (1996) suggest that innovations are not directly linked between them and only the continuity in the R&D expenses ensures the persistence in innovating. The simultaneous inclusion of both the R&D expenses and past innovations variables in our equations thus allows us to test this assumption. Our results finally reject the Cohen & Kleppers' prediction since the R&D score is always significant as well as the feedbacks on patenting. Consequently the persistence in innovating does not reflect only a continuous flow of R&D expenses insofar as the past innovating activities remain significative despite the significance of the R&D expenses. At the firm level, innovations are consequently related between them confirming Duguet & Monjon (2002)'s findings who reject the Cohen & Klepper (1996)'s hypothesis. We now detail the different dynamics of innovation according to our three dependant variables proxying for firms' innovation activity: Non Adjusted, Citations Adjusted and Leader patent counts.

Persistence of Patenting (Non Adjusted patents)

At the simple patent count level, the feedbacks are almost always significant at the 1% level. There is however no evidence of a decreasing persistence following the importance of lags introduced in the equation. When comparing columns 1 and 4, it even seems that the coefficients tend to increase. That means the *Non Adjusted* patenting does not erode itself over the time and consequently that firms are strongly persistent in using patents. More generally such result exhibit the (increasing) importance of patents in pharmaceuticals.

Considering the research efforts, the coefficients of R&D expenditures is always positive and decreases a little as the feedbacks increases. It suggests that the more persistent patenting over the time apparently do not require the largest expenses in R&D. If we hypothesize that some strategic use of patents are at work, the interpretation of the R&D's decreasing coefficient is straightforward: the building of barriers to entry, product development and other foreclosing strategies represent a weak innovative behavior which need few expenditures in R&D, once controlling for firms effects. Such a result suggests the *Non Adjusted* patenting as a whole captures some behaviors that are not related to a pure innovative activity as the strategic patenting and/or innovations.

Considering the firms' market shares, the coefficient tends to increase with the importance of feedbacks. It means most persistent firms in *Non Adjusted* patenting are also those who benefit from the largest market power. Because the amount of sales' coefficient follows the same trend, one may therefore deduct this effect is proper to the firms' size: largest firms are the most persistent in granting *Non Adjusted* patents.

- Table 3 about here -

The dynamic analysis of the *Non Adjusted* patenting seems to support the assumption according to which largest firms (those having the largest level of commercial activity and market share) are those who have the greatest use of patents but without having the research effort that would however be necessary to really innovate in the same proportion. *Table* β thus justifies our methodology—the use of different proxies for firms innovations—by showing that continuous patent flows do not reflect necessarily persistence in innovation but persistence in patenting.

Persistence of Innovating (Citations Adjusted patents)

Similarly with Duguet & Monjon (2004), in our the Citations Adjusted equations, the coefficient of lagged innovations decreases with the importance of the lag introduced in the equation. It suggests some kind of knowledge depreciation takes place and consequently that strong entry barrier to innovation exist. In contrast to their findings, our coefficient however remains almost always significant at the 1% level, regardless of the number of lags (up to four years). Hence the pharmaceutical industry seems to be characterized by a learning-by-doing which is depreciating as time goes on. This result have to be put in relation with the fact that the coefficient of the first lag of the Citations Adjusted patent is particularly strong in contrast with the Non Adjusted patent count but also relatively to additional lags. After two years of lags, the coefficients and their significance seems however less smooth what suggests the persistence in granting Citations Adjusted patents is lower after two years.

Compared with table 3, the coefficient of R&D is stronger and increases significantly with the importance of lags. In addition to the rejection of the Cohen and Kepller's hypothesis, we deduct

that persistence in *Citations Adjusted* patenting reflects indeed a real innovative behavior since firms tend to increase their R&D expenses when the *Citations Adjusted* patenting goes on. This confirms previous findings in the literature (presented earlier): the *Citations Adjusted* patenting is a better proxy for innovation than the whole patenting since it results from higher R&D efforts.

Considering sales and market shares, coefficients are always negative what confirm that largest firms have the lowest technological influence. As the importance of the coefficient of market share increases with the importance of lags, table 4 suggests the more persistent firms in Citations Adjusted patenting are also the smallest: market domination is inversely proportional with the technological influence.

- Table 4 about here -

Results which are presented in *table 4* confirm the importance of smallest firms in the pharmaceuticals' technological dynamics. They seem to be a major source of technological change to the extent that pharmaceutical patents as a whole widely cite their inventions. These inventions tend therefore to have a large impact at the industrial level.

Persistence of Pioneering Behaviors (*Leader* patents)

The estimations on the dynamics of *Leader* patenting (those patents which are more cited and which cite less than the yearly industrial medians) show that the feedbacks have always a negative influence on the current propensity to grant other *Leader* patents but with increasingly small coefficients according to the importance of lags. The firms' pioneering behavior thus tends to reduce further innovative ambitions even if this effect decreases as the time goes on. Hence firms having already granted *Leader* patents have a strong probability, in the short run, to exhibit a zero count of it in the following years (see Salomon & Shaver, 2005 for similar interpretations in another context). This is straightforward to interpret: some firms canalize their innovative effort (R&D expenditures for instance) for some occasional technological breakthroughs which then limit their future inventive capacities in the short run.

Consequently the pioneering behaviors seem to be not bearable by the firms for each period. It is possible that the time needed to create a technological breakthrough does not allow persistence from one year to another. Another explanation is supported by the coefficients of the R&D expenditures that show the *Leader* patenting needs exceptional expenses in research that are probably not bearable continuously. The coefficients of R&D are indeed the strongest compared with other proxies for innovation: the quality ranking of innovation thus follow that one of the R&D expenses.

- Table 5 about here -

Table 5 shows larger investments in R&D are needed to grant Leader patents compared to other innovations. The main finding concerns the deterring effect of past pioneering behaviors on the current Leader patenting. When comparing this result with column 9 of table 2 we can however deduce that pioneering firms belong to a quite stable group since the Leader patent stock is significantly positive to explain the Leader patenting.

4.3 Overall Results

In general one may consider that persistence in innovative activities shed light on the presence of barriers to entry since a technological dynamics exists at the firm level. This interpretation of the persistence in innovative activities is consistent with the coefficients on the *Self Citations* in table 2 which show that smaller innovations often cites the firms' previous inventions. Hence in some cases the persistence is strong but decreasing (*Citations Adjusted* patent), in some other cases the persistence is weaker but increasing (*Non Adjusted* patents) whereas it can be negative revealing a dynamic deterring effect of some innovations (*Leader* patents) which decreases with the number of lags.

The impact of size and market power found in table 3 are confirmed in the dynamic equations.

Whereas the amount of sales (the firm's level of commercial activity) increases the probability to grant patents, with increasingly important coefficients according to the number of lags, it reduces

the probability to influence the technological change: the coefficients are always negative concerning the quality patents (*Citations Adjusted* and *Leader*). The role played by the market dominance is the same, even if in both cases the coefficients are stronger.

As a result, whereas the market power increases the probability to be persistent in granting patents, it decreases the propensity to provide highly influent patents and this effect increases with the importance of feedbacks. This is a key result of the paper insofar as it sheds light on the effect of market dominance on innovation in pharmaceuticals. Dominant firms are indeed persistent only for low quality innovations, suggesting a strategic use of patents to maintain revenues that are presumably threatened by generic entry. Dominant firms do not have a strong technological influence and the smaller firms are apparently the real sources of technological change.⁴⁷

An interpretation of these results indicates larger pharmaceutical firms innovate in a closed loop (see Fudendberg & Tirole, 1984) that leads them to have a strategic management of their knowledge and innovative capacities. Innovations are thus linked between them at the firm level and large firms seem experience research inertia. Whereas the persistence of low quality innovations is found to be strong, the pioneering patenting deters further Leader inventions even if, considering stocks, these breakthroughs seem to be the fruit of the same group of innovators. The strategic use of patent (or more generally the strategic innovations) seems therefore play a significant role in pharmaceuticals, especially for firms having the largest commercial activity.

4.4 Extensions

To refine the analysis on the *Non Adjusted* patent count several additional regressions of equations (4) and (6) have been implemented by excluding *Leader* patents from the firms' *Non Adjusted* patents count.⁴⁸ In these regressions the dependant variable is thus the *Follower* patents flow as being all the patents granted excepting the *Leader* ones. These regressions primarily aimed at checking if the firms' importance was really correlated with the lowest quality patents. For comparison we thus carried out estimations on the *Follower* patents as being a measurement even

⁴⁷Similar conclusion where found with linear IV-GMM in an earlier version of this paper.

⁴⁸The use of the level of employment instead of the level of sales to take into account the firms' size has also been tested and give similar results; we kept however the level of sales because it also take into account the commercial activity. The tables of all these regressions are available uppon request.

more antagonistic with the Citations Adjusted patent count. The results reinforce the preceding conclusions: persistence is appreciably stronger (the coefficient is 0.32 with feedbacks of four years versus 0.26 for the whole patent count), the coefficients of total sales are also higher and especially that one of the market share. Parallel to that the coefficients of R&D expenses are naturally less important (but still significant) whereas the index of Originality is more important what justifies the evoked assumption according to which the Originality index is sensitive to the volume of backward citations. The exclusion of Leader patents from the Non Adjusted patent count then does not reject the assumption according to which patent may have a strategic dimension for largest firms and that its broadest use does not reflect necessarily a richest innovative activity.

5 Concluding Remarks

This paper analyzes the American pharmaceutical firms' persistence in innovating just before the wave of mergers and acquisitions that have followed the "biotech revolution" (known as the "third wave"). We evaluate the impact of past innovative activity on firms' innovation propensities using a non-linear GMM estimator for exponential models that allows for predetermined regressors and linear feedbacks. Hence, an empirical investigation on Non Adjusted, Citations Adjusted and "Leader" patents has been presented both on innovation propensities and persistence in innovation. We find that innovative activity at the firm level depends strongly on the size of past innovations. The results also shed light on the importance of small firms in the dynamics of innovation in pharmaceuticals, and suggest that large firms persist in using patents strategically in order to preserve their revenues by evergreen their commercialized products. Pharmaceutical innovation in general, and pioneer innovation in particular, depends thus largely on past quality innovation made by firms, and this effect may likely deter further Leader innovations rather than strengthen incentives to invest on pioneering invention. In addition, the strategic use of patents seems to be an important feature of the pharmaceutical industry and well announce the wave of concentration that follows our period of analysis which will be explored in further works.

The estimates suggest that in the pharmaceutical industry the "displacement effect" is likely to dominate the potential "efficiency effect" attributed to market dominant firms when we relax the

patent homogeneity assumption. Further, (large) pharmaceutical firms may find it more profitable over time to make incremental innovation –product developments and strategic innovations– rather than high quality innovations. When considering how persistently pharmaceutical firms innovate, the functioning of innovation seems to support the hypothesis that the pioneering behavior, at the firm level, is not persistent whereas the *Citations Adjusted* patenting is eroding on the short run and the simple patent count appears to be more stable over the time. A key result of the paper is thus that technological breakthroughs need large investments in R&D that limit the ability of firms to be persistent sources of radical technological change (from one year to another). However, the *Leader* patenting seems to come often from the same firms as evidenced by the positive impact of *Leader* patent stocks. The *Citations Adjusted* patenting is rather persistent over time but seems essentially provided by the small firms' inventive efforts.

This result extent to the pharmaceutical industry the findings of Lerner (1997) who finds that in the disk drive industry the firms who follow the (technological) leader display the greatest propensity to innovate. Consequently technological followers appear to be those which grant the most patents whereas the real technological change seems to be the fruit of a non (or weak) persistent process in the short run. Our results thus confirm the advanced hypothesis of increasing difficulties to innovation in the pharmaceuticals, especially for incumbent firms who commercialize more and more low innovative products. Such a finding could be related to diseconomies of R&D and organizational inertia related to big laboratories.

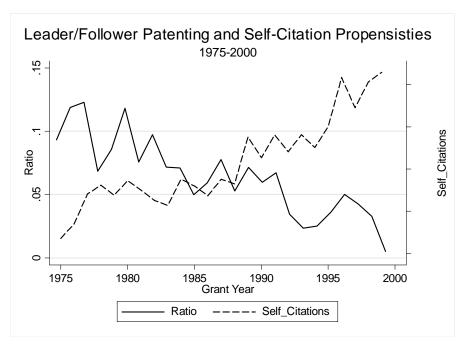
Finally, there are implications for patent policy, particularly the questioning of the optimal patent length as well as the optimal scope of protection offered by patents. Additional follow up research may also be considered. A first step will be to assess the impact of our proxies of innovation on the firms' financial performance. Secondly, an analysis of the relationship existing between entrant and incumbent firms is needed to fully understand the strategies that are currently emerging in the drug industry. To this end, mergers and acquisitions and other technological interactions between firms should also be considered.

Appendix

Table 1. SUMMARY STATISTICS

Patenting Firms T3 (77 firms)	Obs.	Mean	Standard Dev.	Min.	Max.
Sales	1085	2786.416	5362.877	0	43992.59
Market Share	1085	.5094704	.9133403	0	4.717773
R&D Expenditures	1085	283.2219	546.97	0	4833.788
Originality (mean)	1085	.0950629	.17544	0	.8175583
Citations received (nor.)	1085	78.10945	216.2227	0	2098.684
Patents	1085	5.621198	14.67009	0	115
Leader patents	1085	.4562212	1.493272	0	21
Follower patents	1085	5.164977	13.57932	0	108
Citations Share	1085	.0069771	.0186747	0	.1871287
Patent Stock	1085	25.35753	68.66387	0	536.527
Citations per Patent	1085	6.116834	13.78752	0	135
Citations stock/Patent	1085	22.92756	52.56765	0	352.5332
R&D Stock	1085	1084.876	2269.905	0	15166.15
Leader Patents Stock	1085	2.623058	7.080935	0	56.64452
Follower Patents Stock	1085	22.73448	62.20354	0	485.4362

Figure 2



Source: Author's calculations from NBER Patent Data File

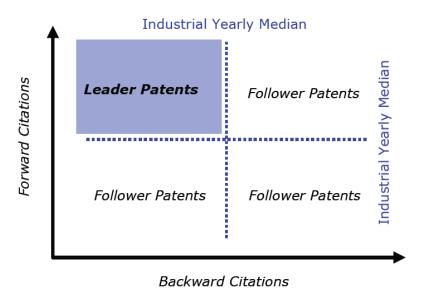


Table 2 : GMM-Wooldridge Estimation
Patenting and Quality-Adjusted Patenting Propensities: Pharmaceutical Firms (1975-1991)

	Non-Adjusted Patents C		Citations-Ad	Citations-Adjusted Patents		Leaders Patents	
	(N	(A)	(CA)		(L)		
	1	2	3	4	5	6	
Log (SALES)t-1	0.2758	0.2507	-0.2335	-0.2192	-0.3081	-0.3456	
- ` '	(0.0638)***	(0.0623)***	(0.0164)***	(0.0215)***	(0.1584)*	(0.1549)**	
Log (R&D)t-1	0.1846	0.2146	0.3058	0.3629	0.9776	1.0400	
	(0.0550)***	(0.0405)***	(0.0142)***	(0.0238)***	(0.1477)***	(0.1814)***	
Market Share t-1	0.5459	0.3713	-0.2075	-0.2879	-0.2428	-0.4529	
	(0.0298)***	(0.0522)***	(0.0135)***	(0.0213)***	(0.3115)	(0.4604)	
Citations Share t-1	9.2923	6.8644	0.6351	-2.4173	47.0613	6.1456	
	(0.6046)***	(0.6976)***	(0.0626)***	(0.1667)***	(27.5860)	(19.2542)	
Originality t-1	1.6099	1.5240	0.3372	0.1583	3.5190	4.0000	
	(0.0985)***	(0.0729)***	(0.0106)***	(0.0278)***	(1.3130)**	(0.9435)***	
Self Citations t-1	0.4379	0.2014	0.1502	-0.4582	1.5176	1.1011	
	(0.0601)***	(0.0636)***	(0.0067)***	(0.0645)***	(1.4166)	(1.1022)	
GNA t-1		0.0053					
		(0.0005)***					
GCA t-1				0.0067			
				(0.0001)***			
GL t-1						0.1327	
						(0.0547)**	
AR(1)	-2.2778**	-2.3046**	-2.0369**	-2.1770**	-1.2404	-1.2474	
AR(2)	1.4769	1.4097	-1.0756	-1.6421	0.6215	0.5661	
Sargan Overid. Test	39.9866	41.4776	44.6007	43.0607	14.6936	14.7414	
DOF	41	41	41	41	14	14	
Number of Observations	854	854	854	854	854	854	
Number of Firms	$\gamma\gamma$	$\gamma\gamma$	$\gamma\gamma$	77	$\gamma\gamma$	$\gamma\gamma$	

Robust Standard Errors in parentheses. GNA, GCA, GL are depreciated patents stocks. * significant at 10%; *** significant at 1%

Estimation has been implemented using ExpEnd Gauss Code (Windmeijer, 2002).

 ${\bf Table~3:~GMM\text{-}Wooldridge~Estimation}\\ {\bf Non~adjusted~Patenting~(Persistence~to~Patent):~Pharmaceutical~Firms~(1975-1991)}$

	Non-Adjusted Patents (NA)				
	1	2	3	4	
NA t-1	0.2194	0.2212	0.1580	0.2594	
1111 0 1	(0.0073)***	(0.0323)***	(0.0234)***	(0.0306)***	
NA t-2	(0.0010)	0.4256	0.0575	0.3308	
1111 0 2		(0.0391)***	(0.0139)***	(0.0417)***	
NA t-3		(0.0001)	0.0381	0.0027	
1111 0 0			(0.0162)**	(0.0211)	
NA t-4			(0.0102)	0.2836	
1111 0 1				(0.0185)***	
Log (SALES) t-1	0.2019	0.3135	0.2280	0.2746	
Log (SILLS) VI	(0.0647)**	(0.0641)***	(0.0658)***	(0.0951)**	
Log (R&D) t-1	0.2628	0.2893	0.3419	0.2916	
Log (ICCL) t I	(0.0574)***	(0.0675)***	(0.0675)***	(0.1035)**	
Market Share t-1	0.5930	0.3881	0.5195	0.6838	
Warner Share C1	(0.0557)***	(0.1234)**	(0.0611)***	(0.2022)***	
Citations Share t-1	3.0054	40.4953	-1.3427	8.0792	
	(0.2219)***	(3.2367)***	(0.7817)*	(3.2081)**	
Originality t-1	2.0976	2.5207	2.8708	3.3847	
originality t i	(0.0962)***	(0.4321)***	(0.2813)***	(0.6392)***	
Self Citations t-1	-0.0624	0.2202	-0.3366	-0.6691	
Sen Citations v 1	(0.0519)	(0.2202)***	(0.0930)***	(0.2783)**	
	(0.0010)	(0.2202)	(0.0000)	(0.2100)	
AR(1)	-2.7849**	-2.2537**	-2.2924**	-1.8295*	
AR(2)	1.2923	0.2497	1.2109	0.9240	
Sargan Overid. Test	43.6485	38.9202	31.5590	35.7278	
DOF	42	39	36	33	
Instrumental Variables	8	9	10	11	
Number of Observations	854	$\gamma\gamma\gamma$	700	627	
Number of Firms	$\gamma\gamma$	77	73	68	

Robust Standard Errors in parentheses.

* significant at 10%; ** significant at 5%; *** significant at 1%

Estimation has been implemented using ExpEnd Gauss Code (Windmeijer, 2002).

Table 4: GMM-Wooldridge Estimation

Citations-Adjusted Patenting (Persistence to Innovate): Pharmaceutical Firms (1975-1991)

	Citations-Adjusted Patents (CA)			
	1	2	3	4
CA t-1	0.8010	0.7674	0.9411	0.7967
CA t-1	0.8019	0.7674	0.8411	0.7867
CA t-2	(0.0037)***	(0.0035)*** 0.0340	(0.0032)*** 0.0551	(0.0039)*** 0.0559
CA 1-2		(0.0039)***		(0.0085)***
CA t-3		(0.0039)	(0.0069)*** -0.0010	-0.0018
CA t-3			(0.0076)	(0.0075)
CA t-4			(0.0076)	0.0062
CA 1-4				(0.0033)*
Log (SALES) t-1	-0.2765	-0.2470	-0.2841	-0.2431
Log (SALES) t-1	(0.0164)***	(0.0346)***	(0.0759)***	(0.0833)**
Log (R&D) t-1	0.4746	0.4644	0.5565	0.5854
Log (R&D) t-1	(0.0232)***	(0.0291)***	(0.0690)***	(0.0841)***
Market Share t-1	-0.4258	-0.5545	-0.6290	-0.6595
Market Share t-1	(0.0175)***	(0.0327)***	(0.0552)***	(0.0615)***
Citations Share t-1	-6.3376	-2.6953	-6.0990	-3.0237
Citations Share t-1	(0.2208)***	(0.4687)***	(0.4690)***	(0.7494)***
Originality t-1	0.0269	0.2239	0.1575	0.3415
Originality t-1	(0.0384)	(0.0468)***	(0.1123)	(0.1056)**
Self Citations t-1	0.0815	0.2318	0.1957	0.4766
Self Citations t-1	(0.0583)	(0.0565)***	(0.2039)	(0.2403)*
	(0.0000)	(0.0000)	(0.2000)	(0.2100)
AR(1)	-2.8642**	-2.6623**	-2.6830**	-2.5109**
AR(2)	-0.7149	-1.0598	-1.2019	-1.2582
Sargan Overid. Test	46.3420	42.3981	39.8911	34.0426
DOF	42	39	36	33
Instrumental Variables	8	9	10	11
$Number\ of\ Observations$	854	$\gamma\gamma\gamma$	700	627
Number of Firms	$\gamma\gamma$	$\gamma\gamma$	73	68

Robust Standard Errors in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%

Estimation has been implemented using ExpEnd Gauss Code (Windmeijer, 2002).

Table 5: GMM-Wooldridge Estimation
Pioneer Patenting (Persistence to Open Tech.Path): Pharmaceutical Firms (1975-1991)

Pioneer Patenting (Persistence to Open Tech.Path): Pharmaceutical Firms (1975-1991)					
	Leaders Patents (L)				
	1	2	3	4	
	0.0000	0.0740	0.4000	0.5050	
Lt-1	-0.3369	-0.2749	-0.4830	-0.5379	
	(0.0602)***	(0.0533)***	(0.0668)***	(0.0692)***	
Lt-2		-0.1150	-0.4145	-0.3880	
		(0.0359)***	(0.0215)***	(0.0346)***	
Lt-3			-0.3304	-0.3476	
			(0.0274)***	(0.0272)***	
Lt-4				-0.0090	
				(0.0446)	
Log (SALES)t-1	-0.1311	-0.2205	-0.0252	-0.1372	
	(0.1174)	(0.1665)	(0.1246)	(0.1217)	
Log (R&D)t-1	0.7589	1.0422	0.6110	0.8674	
, ,	(0.1108)***	(0.1606)***	(0.1141)***	(0.1463)***	
Market Share t-1	0.7317	-0.1040	0.5331	0.3549	
	(0.4767)	(0.3140)	(0.3789)	(0.3198)	
Citations Share t-1	1.5049	-0.6474	1.8712	1.9788	
	(1.6224)	(1.5049)	(2.0462)	(2.2969)	
Originality t-1	2.9983	3.9153	1.3071	1.6606	
	(0.6544)***	(0.9106)***	(0.2068)***	(0.3225)***	
Self Citations t-1	2.2774	0.6719	0.5079	0.1711	
	(0.0533)***	(0.2354)**	(0.2496)**	(0.2396)	
AR(1)	-0.9598	-0.9847	-1.3617	-1.1248	
AR(2)	0.3017	0.9289	1.1675	0.6704	
Sargan Overid. Test	16.0015	16.8592	19.3368	17.4663	
DOF	15	14	13.5500	12	
Instrumental Variables	8	9	10	11	
Number of Observations	854	777	700	627	
Number of Firms	77	77	73	68	
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Robust Standard Errors in parentheses.

* significant at 10%; ** significant at 5%; *** significant at 1%

Estimation has been implemented using ExpEnd Gauss Code (Windmeijer, 2002).

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