Reverse causality in the R&D – patents relationship: an interpretation of the innovation persistence

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Abstract
Starting from the failure of the R&D-patents traditional relationship, when time-series and/or within industry dimensions are included in the empirical analysis, the present work tries to contribute to the empirical literature from two directions. Firstly, it performs a Granger causality test based on the theoretical presumption of a reverse patents→R&D link as an explanation for the failure of the traditional relationship. Secondly, assuming the reverse patents-R&D causality, we test and interpret the lag structure of such a relationship which shows the *effective patent life* that firms can expect within the two Schumpeterian patterns of innovations they belong to. In the light of the *effective patent life,* we offer a further explanation of innovation persistence which overturns the findings of the existing literature on persistence.

Keywords: R&D, patents, innovation persistence, Granger causality

JEL Classification: C23, O30

1. Introduction

R&D activity is the basis for the production of innovation that, in its turn, drives economic growth. The innovative process is made up of R&D investments, the *input* of the process, and the innovation, the *output*. The most common measure of the innovation output is the number of *patents*. The traditional direction of causality in the R&D-patents relationship (hereafter R&D→patents) assumes that patents are the natural output of the R&D activity in the sense that more investment in R&D will result in more innovations and patenting (Jaffe, 1986; Griliches, 1990). The empirical literature, performed on cross-sectional data, confirmed a strong and highly significant (contemporaneous) correlation between R&D inputs and different patent measures across firms: the greater the R&D investments, the greater the patents (Pakes and Griliches 1980; Hall *et al.* 1986; Griliches 1988; Beneito 2006).

Recent theoretical and empirical papers drawn attention to some drawbacks in the R&D-patents traditional relationship. New theoretical approaches have shown that, even if in the 1990s there was an increase in patent applications, the tendency to extend patent protections may be counterproductive in terms of R&D investments (Shapiro 2001; Hunt 2006; Bessen and Hunt 2007). From an empirical point of view, when time-series and/or within industry dimensions are included in the empirical analysis, the positive correlation between R&D and patents almost vanishes (Hall *et al.* 1986; Hausman *et al.* 1984; Czarnitzki *et al.* 2009). Some explanations have been advanced in order to justify the failure of the R&D→patents causality direction, in terms of the weaker orientation towards patent protection of some industries (Levin *et al.* 1987) as well as of patent data being "wrong" indicators of innovative activity (Griliches 1990).

We argue that the traditional R&D→patents fail if a reverse causality in the R&D-patents relationship holds: patent applications are made at an early point in the development process and most of the R&D expenditures occur after the patent applications. Only recently the research in this field has started to explore the reverse causality in the R&D-patents relationship (hereafter patents→R&D). If patents are considered as a policy instrument aimed at fostering and stimulating R&D investment and innovation, the analysis of patents→R&D becomes of utmost importance (Encaoua *et al.* 2006). The mainstream of theoretical literature concerning the reverse causality in the patent-R&D relationship assumes a positive correlation. Empirical studies lack corroboration in this conclusion: they tend to be unclear or not in favour of the positive correlation assumption.

The aim of this work is twofold: firstly, it tries to enrich the empirical literature based on the theoretical assumption of a reverse patent→R&D link. Differently from the few foregoing empirical studies, we do not impose the reverse causality relationship between patent and R&D but we perform a Granger causality test whose results corroborate the possibility that a reverse causality in the patent-R&D relationship may exist. As it turns out, the Granger causality test has confirmed that past values of patents contain the information that is relevant for forecasting R&D:, in the Granger sense, patents cause R&D expenditure. Therefore, we can assume that the productivity of the R&D activity, in terms of the share of inventions firms are willing to patent, occurs at an early stage of the innovation process, thus driving up the future timing and intensity of the R&D expenditure.

Secondly, we argue that the lag structure of the reverse causality in the patents and R&D relationship offers a new explanation of the innovation persistence, in terms of Schumpeterian patterns of innovations, that overturns the findings of the existing literature on this subject. Going into more detail, we hypothesize that the lag structure of the reverse causality differs in the two Schumpeterian patterns leading to different interpretations of the innovation persistence. As a matter of fact, the traditional approach states that the "creative accumulation" (as in Schumpeter Mark II) leads to innovation persistence, while the "creative destruction" (as in Schumpeter Mark I) is used to explain the absence of persistence in innovation activities. Even though firms in different industries of the economy face a distinct set of opportunities, constraints and conditions, we argue that those industry-specific characteristics play a fundamental role in explaining *how* and *when* patents stimulate R&D activity for firms. In the light of this fact, according to the characteristics of the technological regimes (Schumpeter Mark I and Schumpeter Mark II) firms belong to, we can interpret the lag structure in the patents→R&D relationship. We may expect that in sectors characterized by a high appropriability of innovations, high barriers to entry and the dominance of large established firms (the Schumpeter Mark II), firms which decide to patent their innovations are more likely to believe that the *effective patent life* (the expected time until a patented product is replaced on the market) will be long (O'Donoghue *et al.* 1998). Therefore, they tend to enjoy the monopoly rent patent give them and postpone the R&D activity until the moment that this monopoly rent is expected to expire. In other words, they do not persist in their R&D investment. On the contrary, in sectors with opposite characteristics (the Schumpeter Mark I), firms believing in a shorter effective patent life may tend to persist in the innovative effort. Hence, the cause of the innovation persistence on R&D, as discussed above, refers to and depends on the *effective patent life* which is then defined by the lag structure in the patents→R&D relationship.

Our empirical analysis is conducted at the micro level on an original dataset of 6490 Italian firms surveyed from 1998 to 2004. We have specified and estimated a log-linear dynamic regression model of the (log of) R&D expenditure on the number of patent applications of firms in the two Schumpeterian patterns.

The estimation results have confirmed our predictions. They have shown the positive and statistically significant coefficient of one year lagged dependent variable (R&D effort) as well as the positive and statistically significant contemporaneous coefficient of the patent applications in Schumpeter Mark I. It implies that there is persistence in the R&D expenditure and such persistence is path dependent since other factors, especially the patenting activity we are interested in, affect the innovation process. However, in Schumpeter Mark II, neither the lagged dependent variable coefficients nor the patent applications coefficients (contemporaneous and up to two years lagged) are significant, indicating the absence of persistence due to the longer *effective patent life* firms expect in this pattern (as the estimated lag structure in the patents→R&D showed). Unfortunately, despite the width of the cross-sectional dimension of the panel, the lack of a reasonable time lag between patents and R&D expenditure may challenge the validity of our results in Schumpeter Mark II. We try to give robustness to the analysis by showing that, controlling for lots of aspects affecting the patent-R&D relationship, none of such controls grasps the variance of R&D expenditure for firms in Schumpeter Mark II.

The paper is organized as follows. Section 2 reviews the literature that provides the background and foundation for our study; section 3 describes the Schumpeterian patterns of innovations where our hypotheses will be tested; section 4 comprises the econometric specifications and results and section 5 contains some concluding remarks.

2. The literature

The main idea that we want to put forward in this paper, is that the lag structure of patent coefficients in the reverse causality between patents and R&D, affects the innovation persistence of R&D expenditure (in the two Schumpeterian regimes) through the *effective patent life*. Hence, there are two overlapping literatures: the patents-R&D relationship and the innovation persistence literature. In the following part we briefly summarize both types of literature in order to highlight the hypotheses that we are going to test.

Patents-R&D relationship literature

The traditional direction of causality in the R&D-patents relationship assumes that patents are the natural output of R&D activity, meaning that more investment in R&D will result in more innovations and patenting (Jaffe 1986; Griliches 1990). The empirical literature confirmed this positive relationship (Pakes and Griliches 1980; Griliches 1988; Beneito 2006). Several papers on cross-sectional data of firms, have estimated the elasticity of patents with respect to R&D to be around 1 (Hausman *et al.* 1984; Jaffe 1986; Duguet and Kabla 1998; Crepon *et al.* 1998; Brouwer and Kleinknecht 1999; Cincera 1997). Hall *et al.* (1986) examine the existence of lags in the R&D→patent finding that, contrary to what would have been expected, only the contemporaneous relation is statistically significant, not the lags.[1] Similar results emerged in cross-country (de Rassenfosse and van Pottelsberghe 2009) and cross-region (Bottazzi and Peri 2003) estimates.

There are two drawbacks in the traditional direction of causality in the R&D→patent. Firstly, if a time-series dimension is included in the analysis, the positive correlation between R&D and patent almost vanishes: the estimated parameters of the reaction of patents to changes in R&D expenditures (over years) fall sharply and become less significant (Hall *et al.* 1986; Hausman *et al.*1984; Czarnitzki *et al.* 2009). Secondly, the above correlation becomes almost absent when the analysis is at the industry level. Levin *et al.* (1987), in justifying the previous evidence, says that, despite of some industries have a high propensity to patent, they patent much fewer than other industries with a weaker orientation towards patent protection.

Griliches (1990) offers two kinds of explanations for the noticeable weakness in the estimated R&D→patent elasticity. One is that patent data are not a "right" indicator of innovative activity because they reflect a propensity behaviour, rather than innovation performance or research productivity.[2] The other concerns patent series which are very random because they vary greatly in their value, with most patents having a low value and only a few patents having a very high value.[3]

In the light of the fact that the empirical evidence has shown the failure of the R&D→patents relationship while taking into account within-industry and/or time-series dimensions, we argue that the undisputed link between patents and R&D may be reversed: patents aim at stimulating the R&D investment; patents encourage investment in R&D and thus the production of knowledge and innovation.

The reverse causality link between patents and R&D was first examined by Nordhaus (1969). He asserted that the extent of patent protection, enhancing the expected return on an innovation, leads to incentivize the R&D investments.

Theoretically, the expectations of the signs of such a reverse causality relationship are twofold. Intuitively, the broader the patent scope or the longer the patent length, the greater the R&D effort is (Denicolo 1996). But, considering the nature of innovations (sequential or independent, complementary or isolated) the results may change (Bessen and Maskin 2009; Hunt 2006; Gallini 2002; Bessen and Hunt 2007).[4]

Shapiro (2001) reinforces the possibility of a negative link between *patent accumulation* (instead of *patent scope* or *length*) and R&D expenditure in industries like semiconductors, software or biotechnology, speaking of a *patent thicket* (as a dense web of overlapping intellectual property rights).

Even if theoretical literature has found justifications and conditions under which the reverse causality in the patent→R&D relationship holds, empirical works lack in confirming either a positive or a negative result. Pakes (1985) suggests a reverse Granger-causality from patents to R&D on the grounds that patents could contain information on technological opportunity that would lead to R&D in the future. Neither Pakes (1985) nor Hall *et al.* (1986) found evidence of causality in this direction. Using two successive four-year apart innovation survey data, Van Ophem *et al.* (2002) found little evidence of a Granger-causality from R&D to patents but clear-cut evidence of a causality in the opposite direction. The empirical study of Kortum and Lerner (1999) justified the patenting surge in 1990s by both an increase in research productivity due to a burgeoning technological revolution and a change in the management of innovation, involving a shift to more applied activities (they test what they call the *fertile technology hypothesis*) rather than R&D spending. Empirical evidence seems to confirm that in technologies as semiconductors or software, characterized by a complex and cumulative process, patents are disadvantageous (Hall and Ziedonis 2001; O'Donoghue *et al.* 1998), while in industries with independent innovation processes, such as chemical and pharmaceutical industries, or with a slower technological pace (e.g. the steel industry), patents seem to foster innovation (Kingston 2001). The first and, to our knowledge, the only empirical work estimating the reverse causality relationship R&D-patents is that of Sakakibara and Branstetter (2001). They both ask if an expansion of a patent's scope induces more R&D effort. Their econometric analysis on Japan's patent law reform concludes that there seems to be no evidence that the strengthening of a patent's scope leads to an increase in R&D spending.

Therefore, the failure of the traditional relationship and the support of the theoretical literature about the possibility of the reverse causality relationship (even if under specific conditions) allows us to put forward the hypothesis that a reverse causality patents→R&D may hold. The first part of this work is to corroborate that hypothesis through a Granger causality test over a sample of Italian firms belonging to various sectors of the economy.

Innovation persistence literature

The persistence of firms in innovative activities occurs when a firm which has innovated in one period innovates once again in the subsequent period. It is, therefore, linked to the success firms have in the research area (Malerba *et al*. 1997; Cefis and Orsenigo 2001). Theoretical literature provides three explanations of the persistence of innovation at the firm level: 1) *sunk cost*: it is stressed that R&D decisions are subject to a long time horizon, and if a firm decides to take up R&D activities, it will incur start–up costs in building up an R&D department or hiring and training R&D staff. These fixed outlays, once made, are usually not recoverable and can therefore be considered as sunk costs (Sutton 1991; Manez Castillejo *et al.* 2004).[5] This approach to innovation persistence implies that in order to build and maintain an R&D department, R&D expenditure must be regular; 2) *financial constraints*: they force firms to retain earning as a source of funds. Therefore, as in the "success-breeds-success" processes (Nelson and Winter 1982), innovative success yields profits that can be reinvested in R&D, thereby increasing the probability to innovate again; 3) *learning-by-doing*: knowledge that has previously been used to produce innovations can be used to produce current and even future innovations.

Those three causes of innovation persistence become relevant in the context of the two Schumpeterian patterns of innovations. Indeed, the studies on the persistence of innovation are motivated by testing the Schumpeter Mark I and Schumpeter Mark II hypotheses that is, authors authors tried to find out whether innovation activities are subject to "creative destruction" or "creative accumulation". Schumpeter Mark I industries are characterized by turbulent environments with relatively low entry barriers where innovations are (mostly) generated and developed by new "entrepreneurial" firms. Accordingly, technological competition among firms in Schumpeter Mark I industries assumes the form of "creative destruction" with successful innovating entrants replacing the incumbents. Vice versa, Schumpeter Mark II industries are characterized by stable environments with relatively high entry barriers in which innovations are generated and developed by large established firms. In Schumpeter Mark II industries technological competition assumes the form of "creative accumulation" with incumbent firms introducing innovations by means of a process of progressive consolidation of their technological capabilities along well established technological trajectories.[6]

According to such features, the traditional literature stated that in Schumpeter Mark I, the "creative destruction" explains the absence of persistence, whereas in Schumpeter Mark II, the existence of significant degrees of persistence contributes to generate the processes of "creative accumulation".

Empirical studies on the persistence of innovation is quite recent. This new area of research was opened by Malerba *et al.* (1997). Successive works provide mixed results about such persistence. Most works that have focused on patenting data, identify weak elements of persistency. Using UK firms in the period 1969-1988, Geroski *et al* (1997), found that only a minority of firms is persistently innovative; Cefis (2003) and Cefis and Orsenigo (2001) investigated, through the transition probability matrix, the probability that firms that have applied for a patent at time t-1 have a stronger probability of applying for a patent at time t+1 than firms that did not apply for a patent in the prior period having found little persistence; Latham and Le Bas (2006) show that innovation persistence is linked to the size and profitability of firms.

On the contrary, empirical analyses based on survey data find a stronger evidence of innovation persistence, but they stress that results are sensitive to the chosen indicator (Duguet and Monjon 2004). Roper and Hewitt-Dundas (2008) showed that both product and process innovations are strongly persistent; Peters (2009) confirms the strong persistence of innovation activities in terms of innovation inputs, in terms of R&D activities, and innovation outputs as measured by the number of innovations introduced by German manufacturing and service firms in the years 1994-2002. However, Raymond *et al.* (2010) findings suggest that there is no evidence of persistence, but the shares of sales stemming from innovative products, introduced in the past, have a small effect on the current shares of sales of innovative products. Also, Antonelli *et al.* (2012), on a sample of 451 Italian manufacturing companies observed during the years 1998-2006, found the presence of significant persistence in innovations.

Having touched on the two relevant theoretical and empirical types of literature, we can now introduce the second and the newest part of this work in which we advance the hypothesis that the lag structure of the reverse relationship between patents and R&D may offer a further explanation of the innovation persistence of R&D expenditure in terms of the *effective patent life*. We hypothesize that the *effective patent life* depends on the different characteristics of appropriability, the barriers to entry and the dominance of large established firms on markets and industrial sectors which are the features of the *technological regimes* in which these firms operate.

The kind of classification of sectors that we use is a relevant part of this work. A *technological regime* is defined as the technological environment in which innovative activities take place in each sector of the economy (Nelson and Winter 1982; Winter 1984, 2006; Malerba 2002). The literature states that innovation process differs across sectors in terms of various dimensions (Pavitt 1984; Mowery and Nelson 1999; Malerba 2004). The dimensions are: 1) Level of technological opportunities; 2) Appropriability conditions; 3) Cumulativeness conditions; 4) External sources of opportunities.[7] Those characteristics provide a set of opportunities and constraints for firms which shape their innovative activities (Cohen and Levin 1989; Malerba and Orsenigo 1995; Lee and Lim 2001). Malerba and Orsenigo (1997) suggested that the notion of technological regimes may be a fruitful concept for studying the different ways in which innovative activities are organized and industries evolve over time. They single out the two Schumpeterian patterns of innovations: Schumpeter Mark I and Schumpeter Mark II. Indeed, the patterns of innovations, originally pointed out by Schumpeter (1934, 1943), were modeled on the properties of technological regimes. The high ease of entry in the market and the low concentration of innovative activity make the *Schumpeter Mark I* very dynamic, with new and more productive innovators replacing the exit firms. the Schumpeter Mark II displays opposite features; it is characterized by high barriers to entry for new innovators, high concentration of innovative activity and a stable population, mainly formed by large and well-established firms. Table 2 below shows the characteristics of the two Schumpeterian patterns of innovations.

Table 2: Schumpeterian patterns

Schumpeter Mark I	***Schumpeter Mark II***
High technological opportunities	Low technological opportunities
Low appropriability	High appropriability
Low cumulativeness	High cumulativeness
Low concentration of innovative activities	High concentration of innovative activities
Low barriers to entry	High barriers to entry
High instability in the hierarchy of innovators	Low instability in the hierarchy of innovators

Relevant for our analysis is that the innovation activity of firms belonging to the same technological regime is homogeneous with respect to the four dimensions above (see Breschi *et al.* 2000). In particular, one can observe almost the same behavior of the innovative activity of firms in the same pattern with respect to the *appropriability conditions* which essentially refers to patents. This aspect is the reason that explains why, in the empirical analysis on the persistence of innovation in terms of the relationship R&D-Patents, we decided to cluster sectors into Schumpeter Mark I and Schumpeter Mark II.[8]

With reference to the literature, we can also argue that the persistence of innovation is related to the characteristics of the technological regime in which the enterprise operates, but we propose a new explanation of such persistence that overturns the previous findings. In detail, the lag structure of the patent→R&D relationship, which is affected by the characteristics of the Schumpeterian patterns, is informative about the *effective patent life* that determines the persistence of innovation of firms. Indeed, in the Schumpeter Mark II regime, high cumulativeness and appropriability conditions create strong technological entry barriers for new innovators. This implies that R&D activity is made by well-established oligopolistic innovators, which may patent their innovations and enjoy the monopoly rent patent gives them; they expect a longer *effective patent life* and, therefore, they may postpone the successive R&D activity just before the monopoly rent expires.[9]

As for the interpretation of the lag structure of the regression of patents on R&D expenditure, we should expect a negative/no contemporaneous and delayed (of at least 2-3 years, depending on the *effective patent life*) relation between them. The consequence of such a longer *effective patent life* is the absence of R&D effort persistence.

In a Schumpeter Mark I pattern, instead, low cumulativeness and appropriability conditions tend to facilitate the frequent entry of new innovative firms. In this highly competitive environment, the ability of firms to continuously innovate becomes a crucial factor. Given the expected shorter *effective patent life*, firms which decide to protect their innovation with patents, persist in their innovative effort. Therefore, according to this pattern, we expect a contemporaneous relationship between patents and R&D expenditure.

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3. Data description

For the empirical analysis we have used an original dataset of about 6500 firms investing in R&D during the period 1998-2004.[10] Firms included in the panel are those declaring a positive amount of *intramural* R&D expenditure; firms spending only in *extramural* research activities are excluded from the dataset. The panel is strongly unbalanced because of how it is created. Indeed, to be included in the dataset, it is enough for a firm to declare a positive amount of *intramural* expenditure within at least, one year. Hence, enterprises investing in *intramural* expenditure only in one year, between 1998 and 2004, show missing values for other years.

Information about the economic activity of firms is derived from firms' balance sheets.

The two most important variables in the empirical analysis are the number of patent applications and the R&D expenditure, both standardized by the number of employees in the R&D division.

Table 3 below shows the distribution of the number of patent applications in the whole sample of firms and in the two Schumpeterian patterns from 1998 to 2004.[11] More than 50% of firms do not apply for a patent, this percentage raises to 61% for firms in the Schumpeter Mark II (hereafter SMII). As the number of patent applications increases, the number of firms reduces; the percentage of firms raises again in the range 6-10 patent applications with almost 9% of firms applying for at least 6 patents. This trend is confirmed looking at the Schumpeterian patterns. It is interesting to notice that the number of firms applying for a small number of patents in a year (from 0 to 10) is greater in Schumpeter Mark I (hereafter SMI), while the reverse happens for more than 10 patent applications. This confirms the dynamic nature of SMI pattern, made up of small innovators who continuously patent a small number of innovations.

Table 3 – Number of patent applications, 1998-2004

	Pooling		*SMI*		*SMII*	
N. Patent applications	**N. firms**	**Percentage**	**N. firms**	**Percentage**	**N. firms**	**Percentage**
0	3902	52.03	2530	48.19	1372	61.00
1	1380	18.40	1047	19.94	333	14.81
2	788	10.51	641	12.21	147	6.53
3	410	5.47	314	5.98	96	4.27
4	206	2.75	153	2.92	53	2.36
5	185	2.47	141	2.69	44	1.96
6 to 10	338	4.51	249	4.74	89	3.96
11 to 20	175	2.33	121	2.30	54	2.40
>20 and <50	115	1.53	54	1.03	61	2.71
Total	**7499**	**100**	**5250**	**100**	**249**	**100**

Figure 1 shows the mean of the number of patent applications during 1998-2004, in percentage; it has an increasing trend, with a peak in 2003. This tendency does not change when we split firms in two technological patterns. It is clear that, firms in SMI have patented more than those in SMII, with a mean difference of more than 9%.

Fig. 1 – Percentage of mean number of patent applications, 1998-2004

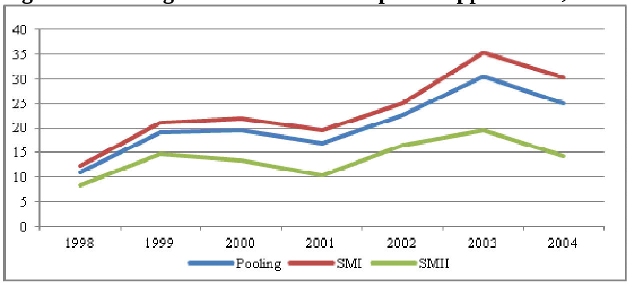
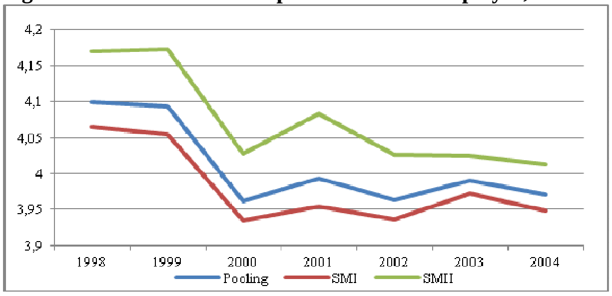


Figure 2 displays the mean, over firms, of the R&D expenditure (over the employees in R&D division)[12] over the period 1998-2004, pooling and for the two Scumpeterian patterns of innovations. We have chosen to standardize R&D expenditure by the employees in R&D division since this measure reflects the overall resources that personnel in R&D use to develop new products and processes.[13] This variable expresses productivity better than others: we may expect that firms investing more in R&D expenditure per R&D employee should be more productive. This variable properly addresses the link between R&D and patents.

Fig. 2 – Mean of the R&D expenditure/R&D employee, 1998-2004



Thus, this sample analisys seems to show that firms in SMI have patented more and invested in R&D less than firms in SMII.

4. Econometric specifications and results

4.1 Granger causality test

Most of the results in the R&D-patents traditional relationship do not take into account the issue of causality in the Granger sense. In recent years significant improvements in the econometric modeling of the Granger causality relationship have been made. Starting from the work of Granger (1969), a lot of studies offer new approaches for testing the Granger causality in panel data.[14] Relying on previous studies, we have attempted to assess the direction of the causality, in the Granger sense, for the R&D-patent relationship. Thus, we have carried out the Granger causality test on the relationship between firms' R&D investment and firms' patenting activity, using the sample of Italian firms (during the period 1998-2004) mentioned above.

For each firm *i* at time *t* we consider two variables: y_{it}, that measures the R&D productivity (proxied by the ratio between R&D *intramural* expenditure and the employees in R&D activities at the firm level) and x_{it}, that measures the number of patent applications of firms (over the employees in R&D division). The Granger causality test will answer the following question: is it R&D productivity that causes, in the Granger sense, patent applications or not? More generally, variable x is said to Granger cause variable y if, given the past values of y, past values of x are useful to predict y. This means that, in order to predict current values of the dependent variable, the relevant information is contained solely in the time dimension of the regressors.

Therefore, testing Granger causality implies to regress variable y on its own lagged values and on lagged values of x, and to test the null hypothesis that the estimated coefficients of the lagged values of x are jointly equal to zero. At this point, the choice of lags is important. We checked the order of the autoregressive process of the variables of interest: both are AR(2) processes. Firstly, the estimation of model (1)[15] will allow us to establish whether x_{it} Granger causes y_{it}:

$$y_{i,t} = a_i + \sum_{l=1}^{n} \alpha_{l,t} y_{i,t-l} + \sum_{l=1}^{n} \beta_{l,t} x_{i,t-l} + \mu_i + \lambda_t + v_{i,t} \qquad (1)$$

where n is the number of lags (n=2), i is the number of firms in each year, t is time period (1998-2004). According to Baltagi (2005) the random error term is made of an unobservable firm specific (μ_i), time specific (λ_t), and a random error term (v_{it}) which represents measurement errors in the dependent variable and the omitted explanatory variables. It is assumed to be independently and identically distributed with zero mean and constant variance. The firm and time specific effects, μ_i and λ_t, capture firms' heterogeneity and exogenous technological change respectively and are assumed to be independent of each other and of regressors.

If x_{it} will Granger cause y_{it}, the following null hypothesis

$H_0 : \beta_{l,t} = 0 \ \forall n = 1,2 \ and \ \forall t \in [1998, \ldots, 2004]$

must be rejected. If the null is not rejected, the estimate model (1) is the same as the estimate restricted model

$$y_{i,t} = a_i + \sum_{l=1}^{n} \alpha_{l,t} y_{i,t-l} + \mu_i + \lambda_t + v_{i,t}.$$

That is, past values of patents applications do not help to forecast R&D productivity.

At the same time, we will specify the same model as in (1) in order to study whether y_{it} Granger causes x_{it}:

$$x_{i,t} = b_i + \sum_{l=1}^{n} \gamma_{l,t} x_{i,t-l} + \sum_{l=1}^{n} \delta_{l,t} y_{i,t-l} + \mu_i + \lambda_t + v_{i,t} \qquad (2)$$

If R&D productivity will Granger cause patents, the following null hypothesis

$H_0 : \delta_{l,t} = 0 \ \forall n = 1,2 \ and \ \forall t \in [1998, \ldots, 2004]$

must be rejected.

In dealing with panel data analysis, the cross-sectional variation is a crucial issue; this type of variation may be addressed with a fixed effect model because it is captured by distinctive intercepts (Hsiao 1986; Holtz-Eakin, Newey, and Rosen 1988). This procedure is appropriate for panels with particularly short time dimensions ($t<10$). We take this aspect into account in the estimation techniques. Once models (1) and (2) have been estimated, we calculate a Wald statistic in order to assess the causality, as in Dumitrescu and Hurlin (2012). They propose a Granger test for heterogenous panel data models in which, under the null hypothesis of homogeneous non causality, there is no causal relationship for any of the cross-section units of the panel. Under the alternative, there are two subgroups of cross-section units: one characterized by causal relationships from x to y

and another subgroup with no causal relationship from *x* to *y*. The test statistic is defined as the cross-section average of individual Wald statistics associated with standard Granger causality tests based on single time series. The author shows that this statistic has a normal semi-asymptotic distribution even for small T samples.

Results are reported in table 3. The estimates of model (1) are in the first two columns; those of model (2) are in the last two. We have estimated both fixed effects and a dynamic panel data model (respectively depicted as **FE** and **GMM** in table 3). The last row of table 3 shows the F-statistic of the Wald test and the relative p-value in parenthesis. Since our sample is highly unbalanced, we have restricted it to the enterprises that have applied for patents in, at least, five years.[16] Concerning model (1), we may conclude that in the Granger sense, patents cause R&D: the Wald statistic is such that we reject the null hypothesis of non causality at 5% level of significance. Looking at the Wald test for model (2), we cannot reject the null: R&D does not Granger cause patent.[17]

To sum up, Granger causality shows that past values of patents are important in forecasting R&D productivity, but the reverse is not true. Although Granger causality differs from causality, we argue that those findings corroborate our main hypothesis that there may be reverse causality in the R&D-patents relationship.

Table 4: Granger causality

	Dep. Var.: ln(R&D)		*Dep. Var.: Patent*	
	FE	**GMM**	**FE**	**GMM**
ln(R&D) (-1)	0.1416*** (2.75)	-0.2345*** (-5.12)	0.0813 (0.92)	0.0518 (0.61)
ln(R&D) (-2)	-0.1332*** (-2.60)	-0.2064*** (-4.32)	-0.0409 (-0.83)	-0.0588 (-0.73)
Patent (-1)	0.0134 (0.59)	0.0206 (0.79)	-0.0700 (-1.02)	-0.5213*** (-9.33)
Patent (-2)	0.0415** (2.48)	0.0533*** (2.57)	0.0829 (0.85)	-0.1125 (-0.87)
N. obs.	890	627	820	566
Wald test	3.18 (0.04)	7.28 (0.02)	1.16 (0.31)	3.28 (0.19)

Notes. FE stands for fixed effects, GMM is the Arellano-Bond estimator. All regressions contain calendar year dummies (results not reported) and heteroskedasticity corrected standard errors; the time span is 1998-2004. Significant coefficients are indicated by * (10% level), ** (5% level) and *** (1% level).

4.2 Innovation persistence estimation results

In order to check our hypothesis that patents→R&D relationship may offer a further explanation for innovation persistence in terms of Schumpeterian patterns, we have estimated the following log-linear dynamic panel data regression model (see Malerba et al., 1997)

$$\log(R\&D)_{i,t} = \gamma \log([R\&D)]_{i,t-1} + \sum_{j=0}^{2} \beta_j Patent_{i,t-j} + \sum \tau\, controls_{i,t} + \alpha_i + \mu_t + \varepsilon_{i,t} \quad \textbf{(3)}$$

for firm *i* at year *t*. *log(R&D)*, the dependent variable, is the natural logarithm of the *intramural* expenditure in R&D activity and *Patent* is the number of patent applications of firms, both standardized by the number of employees in the R&D division.[18] The former, as explained above, is a measure of the R&D productivity, since it captures how much a firm invests in R&D per employees in the R&D division. Patent applications are a standard measure of patents;[19] for reasons of coherence, we also standardized patent applications by the R&D employees since this ratio reflects how many new products and processes have been developed by each R&D employee. γ, the auto-regression coefficient, represents our measure of persistence. We have also introduced contemporaneous and up to two lags of *Patent*; we cannot add further lags of patent applications because of the many missing values in the panel; increasing the number of lags should drastically reduce the number of observations, making inference impossible to do.[20] Equation (3) has been estimated by the Arellano-Bond technique.[21] We have performed the estimation on two Schumpeterian patterns of innovation, Schumpeter Mark I and Schumpeter Mark II.[22] For each pattern we have introduced control variables in order to check the robustness of our hypothesis. Control variables are:

- the natural logarithm of sales as a measure of the firm's size (*ln(Sales)*);
- the ratio between employees in the R&D division and the total number of employees (in percentage), as a measure of the size of the firm's R&D division (*R&D size)*;
- the percentage of graduated employees in the R&D activities; this captures the level of education of the R&D employees (*Education*);
- two variables that control a firm's specific characteristics relative to: the financial structure (*Leverage*) and the efficiency (*Labour cost*).

There are no economic reasons that account for lags in the relationship between R&D investment and control variables, thus we have estimated them contemporaneously.

Following Antonelli (2008) and Antonelli *et al.* (2012) we can asses that the dynamic of the process might be non-ergodic, that is, an early and successful innovation may have long lasting consequences causing further innovations. Moreover, it must be investigated whether the early innovation is sufficient to produce long lasting consequences or whether effective strategies and events that have been taking place along the process do affect the persistence. In other words, the process may be past dependent and path dependent respectively.

Table 9 in appendix shows the estimation results of equation (3) for the two Schumpeterian patterns of innovations. A crucial assumption for the validity of GMM is that the instruments are exogenous. For that, in order to compute the Sargan test, we firstly estimate equation (3) in the homoskedastic case.[23] The null hypothesis of the Sargan test is that the over-identification restrictions are valid; we do not reject the null and the model is correctly specified.[24] In order to control for heteroskedasticity, every estimated equation in table 9 has robust standard errors. Each column is estimated with a calendar dummy variable in order to control for common shocks for a given year; we do not show the coefficients of such dummies. We have also included dummies for the Italian regions that firms belong to in order to control for an investment localization effect:[25] it is reasonable to believe that firms decide to place their production in one region rather than in another to exploit knowledge spillover. The last row of the table displays the p value of the Arellano–Bond test for second-order autocorrelation in the first-differenced residual; we do not reject the null hypothesis of no second-order autocorrelation.

In columns (a) and (b) we have regressed our dependent variable (*ln(R&D)*) on contemporaneous and one year lagged coefficients of *Patent*, including the standard control variable in an R&D-patent empirical analysis, *ln(Sales)*, and the initial condition, $ln(R\&D)_0$, in order to check if the process is shaped by the first realization of the dependent variable. In columns (c) and (d) we add the second lag of *Patent*. In SMI the lagged *ln(R&D)*, the persistence coefficient, is positive and highly significant: the R&D investment is positively affected by the previous realization of the same variable. However, in SMII the autoregressive coefficient is not significant (except in (d) where it is negative and weakly significant).[26] Those results must be interpreted in the light of the lag structure of the patent→R&D relationship. Firms in SMI show a positive, contemporaneous and highly significant sign of the patent applications coefficient.[27] Firms in SMI mostly operate in small traditional sectors of the economy; the "creative destruction" promotes competition among innovative firms which tends to persist in their innovative activity because of the short *effective patent life* they expect. In particular, in this pattern firms that decide to patent their innovations do it continuously as well as their R&D investments. This is why, in column (a), only the contemporaneous (and not the lagged one) coefficient of *Patent* is significant. Adding one more lag of *Patent* does not change the results: only the contemporaneous coefficient remains significant and its magnitude reduces very little. Therefore the contemporaneous relationship between *Patent* and *ln(R&D)* is the result of a shorter *effective patent life* which is the explanation of the persistence of the R&D effort in this pattern of innovation. The significance of the initial condition (everywhere positive in table 9) shows that the early R&D investment has shaped the process. Moreover the non-ergodic persistence of the *ln(R&D)* is also path dependent because it is affected by contingent factors, such as *Patent* (what we are interested in), and all the control variables we include in the model (as shown in every column in table 9).

On the contrary, in SMII the high appropriability of innovations, raising entry barriers, creates an oligopoly of innovators which tend to patent their innovations in order to enjoy the monopoly rent patent given them. They face a longer *effective patent life* (guaranteed by the absence of competition); therefore R&D investments are postponed just before the expected patent rent is due to expire. As just hypothesized, results in columns (b) and (d) show neither contemporary nor delayed (one and two lags) significant coefficients of *Patent*, justifying a longer *effective patent life*. As a result, the persistence coefficient in this pattern is not significant. The strong significance of the initial condition confirms that, in SMII, the present investment in R&D is affected by the earlier one, strengthening the presumption of a relationship between patent and R&D deferred in time.

We expect a positive sign for *ln(Sales)*: if a firm's size increases, investments in R&D may also increase; it is not significant in either of the patterns. The constant term is always positive and significant.

In columns (e) and (f) we have introduced another control for size: *R&D size* as a measure of the size of the R&D division. Its coefficient is negative and significant in both SMI and SMII and its sign means that the R&D productivity decreases when the relative size of the R&D division increases. This is due to the sunk costs: if the R&D division grows (in percentage), the per capita expenditure in R&D decreases. The magnitude of that coefficient is very low: an increase of 1% in the *R&D size* implies a decrease in the R&D productivity of 0.002% for firms in SMI and 0.001% for firms in SMII. *Patent* coefficients do not change in either SMI or SMII, neither do the variables just expounded, but the magnitude of the contemporaneous coefficient of *Patent* in SMI (the only significant) reduces.

Generally, the R&D division of firms is made up of highly educated people. This is the reason why, in columns (g) and (h), we add the variable *Education* to control for the education levels in the R&D division. A positive correlation between R&D investment and the share of graduated R&D employees is presumed, because graduates receive higher wages than less educated people. As expected its sign is positive, but is significant only in SMI (column g): a unitary increase in the percentage of graduated employees implies an increase of 0.004% in the R&D expenses per employee in the R&D division. The reverse R&D-patents relationship remains robust to the introduction of this control variable; the contemporaneous coefficient of *Patent* in SMI continues to be highly significant and its magnitude slowly decreases when more significant regressors are introduced.

We may argue that investments in R&D are affected by the financial structure of a firm: if getting credit becomes more expensive, a firm will have less money to invest. In columns (i) and (l) we introduce a measure of a firms debt, *Leverage*. Firms use debt as a source of financing; when the leverage increases, a firm is considered more risky. *Leverage* is negative but not significant. As always, nothing changes in the patents-R&D relationship and persistence, and the significant contemporaneous coefficient of *Patent* in SMI continues to decrease.

We also control for a measure of efficiency, *Labour cost* (columns (m) and (n) in table 9). It is significant only in SMI with a negative sign: if labor cost decreases in every division (included R&D), the resources to be invested increase everywhere. This is because a more efficient firm may have a higher financial liquidity and, as a consequence, may invest more in R&D activities. In both patterns nothing changes in the sign and significance of all other regressors.

We performed two further robustnes checks. The first one concerns the estimation method. Arellano and Bover (1995) and Blundell and Bond (1998) developed a system estimator that, using additional moment conditions, is more efficient for datasets with many panels and few periods. We estimate equation (e) for SMI and SMII, including all regressors, with this estimator; the results do not change.[28]

The second robustness check is about the dependent variable. We perform the estimation as in columns (i) and (l) using another standardization for the R&D expenditure (and consequently, for patent applications): R&D expenditure/Sales (thereafter *R&D/Sales* and *Patent/Sales* respectively). *R&D/Sales* is a standard measure of R&D expenditure in the literature;[29] it expresses an intensity. Results are shown in table 10 in appendix. They confirm the previous results both for SMI and SMII. The Sargan test[30] confirms that the model is correctly specified. Notice that in this estimation we change the variable *ln(Sales)* with *ln(Employees)* in order to control for a firm's size. *ln(Employees)* is the natural logarithm of the total employees of firms. We are forced to do this change because of the very high correlation between the new dependent variables *R&D/Sales* and *ln(Sales).*

As said above, we cannot introduce more lags of patent applications because of the insufficient number of observations. For sure, this is a weakness of the present analysis, but we have tried to give robustness to our hypotheses showing that, adding more control variables, the relationship between patent and R&D does not change. Moreover, the estimation of the reverse causality R&D-patents link on a more suitable sample can be the line of a future research.

5. Concluding remarks

The present work fits within two literatures: patents→R&D reverse causality relationship and innovation persistence. It makes advances in the empirical literature on the patents→R&D relationship because, to the best of our knowledge, it is the first that tests a R&D-patents Granger causality on an Italian panel data of firms throughout all sectors of the economy. The Granger test results support the hypothesis that the reverse causality patents→R&D (patents occurring at an early stage of the innovation process, promoting/deterring the R&D activity) may cause the failure of the traditional relationship when time-series and within-industry dimensions are introduced.

It also makes advances in the empirical literature on innovation persistence because the *effective patent life,* defined by the lag structure of the reverse causality relationship between patent and R&D, offers another explanation of the innovation persistence in terms of Schumpeterian patterns of innovation. This new explanation leads to opposite empirical results whith respect to the traditional theory of persistence. While this latter links the "creative destruction" in SMI to the absense of persistence, and the "creative accumulation" in SMII to the presence of the innovation persistence, our results show how the monopoly rent granted by the effective patent life may drive firms, in SMI, to persist in the R&D effort and not to persist in SMII. This is shown respectively by the significance of the auto-regression coefficient in SMI and by the absence of significance of the auto-regression coefficient in SMII. In SMI the estimated reverse causality patents-R&D relationship does not change if we repeatedly include regressors. The contemporaneous coefficient of *Patent* remains highly significant in every specification: the innovation dynamicity of firms in this pattern, drives patenting activity and R&D investment to move contemporaneously. Moreover, almost all the regressors are significant as well as the (positive) initial condition, showing respectively the path and past dependence of the non-ergodic persistence. On the contrary, in SMII, no regressor (except *R&D size*) becomes significant. Taking into account that, in the econometric specification, we have controlled for many aspects of firms (time, regional, size, educational, risk, efficiency), this result (together with the significance of the positive coefficient of the initial condition) reinforces our hypothesis that successive lags of *Patent* (more than two) may explain the variance of the dependent variables.

Given the many missing values of patent applications in the dataset, we cannot estimate more than two lags for *Patent*, therefore we cannot draw conclusions about the effective patent life in SMII. The weakness of the present work may be the basis for a future research.

Acknowledgements

We would like to thank Prof. Erasmo Papagni and Prof. Antonio Acconcia who helped to improve the quality of the paper. We are grateful to Cristiano Antonelli (the editor) and anonymous referees for many useful comments and suggestions. Of course, authors retain the responsibility for errors.

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Appendix

Table 1: Technological regimes dimensions

Level of technological opportunities	These are all the instruments that firms use to protect the results of their innovative activities from imitation. Industries can be sorted by *high* and *low* appropriability conditions. High appropriability conditions refer to the ability firms have to successfully protect innovation from imitation (we are dealing with formal means, such as patents and trademarks, and informal means, such as process secrecy and knowledge
Appropriability conditions	These are all the instruments that firms use to protect the results of their innovative activities from imitation. Industries can be sorted by *high* and *low* appropriability conditions. High appropriability conditions refer to the ability firms have to successfully protect innovation from imitation (we are dealing with formal means, such as patents and trademarks, and informal means, such as process secrecy and knowledge
Cumulativeness conditions	These conditions refer to the possibility that the innovative activity today is the starting point for innovative activity tomorrow, that is, firms which are willing to innovate today, are willing to innovate in the future (Cefis and Orsenigo, 2001).
External sources of opportunities	External sources of opportunities arise when firms are able to engage in interactions and co-operations with other agents in the innovation system. The economic environment which may offer a pool of advanced knowledge is made up of suppliers, users, competitors, private R&D labs, universities and other public research institutes (Laursen and Meliciani, 2002; Reichstein and Salter, 2006).

Table 5: Variables and descriptive statistics

Variable		**Mean**	**Std. Dev.**	**Cross-section Units**
ln(R&D)	R&D intramural expenditure over employees in the R&D division (logarithm)	4.00	0.61	6490
Patent	Number of patent applications over employees in the R&D activities	0.21	0.57	3827
ln(Sales)	Natural logarithm of sales	9.32	4.12	5904
RD Size	Employees in the R&D activities over total employees (percentage)	27.4	191.4	5191
Education	Graduated over total employees in the R&D activities (percentage)	36.5	32.1	6490
Leverage	Ratio between total assets and total assets minus total liabilities	8183	65222	5498
Labour cost	Wages over total employees	7305	185441	5817

Notes. Monetary values are in thousands of euros at constant price 2000.

Table 6: Descriptive statistics for SMI and SMII

	SMI			**SMII**		
	Mean	**Std. Dev.**	**Cross-section Units**	**Mean**	**Std. Dev.**	**Cross-section Units**
ln(R&D)	3.97	0.60	4431	4.06	0.64	2059
Patent	0.24	0.61	2684	0.14	0.47	1143
ln(Sales)	9.30	4.08	4041	9.35	4.19	1863
RD Size	27.4	185.7	3572	27.3	203.4	1619
Education	31.5	30.6	4431	47.1	32.5	2059
Leverage	7693	50349	3778	9299	90350	1720
Labour cost	6253	46100	3983	9659	326421	1834

Table 7: Correlations

	ln(R&D)	*Patent*	*R&D Size*	*Education*	*ln(Sales)*	*Leverage*	*Labour cost*
ln(R&D)	1						
Patent	0.0342*	1					
R&D Size	-0.0117	-0.0177	1				
Education	0.0875*	-0.0041	0.0637*	1			
ln(Sales)	0.1867*	0.0033	-0.0831*	0.0121	1		
Leverage	-0.0066	-0.0178	0.0058	-0.0137	-0.0585	1	

Labour cost	0.0305*	0.0019	-0.0155	-0.0096	0.0796*	-0.0059	1

Notes. Star denotes the correlation coefficients significance at, at least, 5% level.

Table 8: Definition of the Schumpeterian patterns

Schumpeter Mark I	mining; textiles; clothing; leather and footwear; wood and related products; printing and publishing; non-metallic mineral products; fabricated metals; machinery and equipment; electrical; radio and TV; medical and optical; other transport equipment; furniture; recycling; construction; wholesale trade; land transport; auxiliary transport services; research and development; plastic material; water; car retails; car wholesale; insurance and supporting activities; real estate; public services; education.
Schumpeter Mark II	motor vehicles; food and beverages; pulp and paper; basic metals; sea transport; air transport; telecommunication; computing and software; other business services; coke and oil; chemicals; electric-powered and gas; retails; transport; financial activities; healthcare.

Table 9: Estimation results. Dependent variable: *ln(R&D)*

	SMI	SMII	SMI	SMII	SMI	SMII	SMI	SMII	SMI	SMII	SMI	SMII
	(a)	**(b)**	**(c)**	**(d)**	**(e)**	**(f)**	**(g)**	**(h)**	**(i)**	**(l)**	**(m)**	**(n)**
ln(R&D) (-1)	0.3085***	-0.0251	0.4273***	-0.4600*	0.4648***	-0.3595	0.4658***	-0.3415	0.4909***	-0.3046	0.4584***	-0.2774
	(2.96)	(-0.17)	(2.98)	(-1.95)	(3.16)	(-1.56)	(3.20)	(-1.46)	(3.07)	(-1.05)	(2.93)	(-0.97)
Patent	0.1369***	0.0232	0.1236***	0.1145	0.1221***	0.0741	0.1107***	0.0770	0.1072***	0.1221	0.1021***	0.1229
	(4.17)	(0.35)	(2.93)	(0.93)	(2.86)	(0.63)	(3.03)	(0.67)	(3.11)	(1.20)	(2.91)	(1.17)
Patent (-1)	0.0008	-0.0873	0.0152	-0.0448	0.0138	-0.0885	0.0283	-0.0917	0.0399	-0.1983	0.0429	-0.1895
	(0.03)	(-1.56)	(0.41)	(-0.35)	(0.36)	(-0.72)	(0.78)	(-0.76)	(0.99)	(-0.51)	(1.11)	(-0.48)
Patent (-2)			-0.0160	-0.0491	-0.0135	-0.0779	-0.0173	-0.0809	-0.0006	-0.0338	0.0027	-0.0356
			(-0.35)	(-0.60)	(-0.30)	(-0.93)	(-0.41)	(-0.98)	(-0.02)	(-0.38)	(0.07)	(-0.39)
ln(Sales)	-0.0023	0.0030	-0.0090	0.0052	-0.0082	0.0034	-0.0082	0.0038	-0.0073	0.0002	0.0069	-0.0069
	(-0.54)	(0.55)	(-1.48)	(0.67)	(-1.35)	(0.44)	(-1.38)	(0.53)	(-1.21)	(0.03)	(0.77)	(-0.76)
R&D size					-0.0020***	-0.0012**	-0.0019***	-0.0012*	-0.0021**	-0.0010**	-0.2096***	-0.0999**
					(-3.46)	(-2.00)	(-3.58)	(-1.94)	(-2.42)	(-2.17)	(-2.56)	(-2.19)
Education							0.0048**	-0.0019	0.0060***	-0.0018	0.0060***	-0.0019
							(2.40)	(-0.50)	(2.66)	(-0.44)	(2.71)	(-0.46)
Leverage									-7.12e-07	-2.86e-07	-6.36e-07	-3.40e-07
									(-0.98)	(-0.60)	(-0.89)	(-0.68)
Labour cost											-3.31e-06*	1.83e-06
											(-1.75)	(0.85)
$ln(R\&D)_0$	0.6922***	1.0193***	0.5863***	1.4801***	0.5622***	1.3936***	0.5232***	1.3957***	0.4874***	1.3601***	0.5039***	1.3458***
	(6.66)	(7.22)	(4.00)	(6.55)	(3.77)	(6.27)	(3.03)	(6.32)	(2.90)	(4.77)	(3.05)	(4.68)
N. obs.	814	359	404	186	401	184	401	184	375	170	372	170
N. firms	414	359	212	95	209	93	209	93	195	86	193	86
p-value 2^{nd} order autocorrelation	0.2460	0.8570	0.7286	0.2569	0.8628	0.3273	0.4963	0.3700	0.2556	0.2140	0.2032	0.2966

Notes. Arellano-Bond dynamic panel-data estimations with robust standard errors. The dependent variable is log of R&D intramural expenditure per employee in the R&D division. The definition of the variables is in table 5. All regressions contain calendar year dummies (results not reported); the time span is 1998-2004. Standardized normal z-test values are in parentheses; significant coefficients are indicated by * (10% level), ** (5% level) and *** (1% level).

Table 10: Estimation results. Dependent variable: *ln(R&D/sales)*

	SMI	SMII
ln(R&D/sales) (-1)	0.1144* (1.91)	0.0351 (0.49)
Patent	13.9456** (2.51)	2.4768 (0.79)
Patent (-1)	-1.3402* (-1.84)	0.7679 (0.24)
Patent (-2)	-0.5113 (-1.05)	-3.9014 (-1.38)
ln(employees)	0.1341 (0.11)	-2.6990 (-1.23)
R&D size	-0.0029 (-1.61)	-0.0544*** (-7.40)
Education	-0.0019 (-0.18)	-0.0381 (-1.44)
Leverage	1.67e-06 (0.34)	2.88e-06 (0.72)
Labour cost	-0.0001*** (-18.75)	-0.0001*** (-15.02)
ln(R&D)$_0$	1.5075 (0.47)	-6.3664 (-1.12)
N. obs.	319	145
N. firms	168	76
p-value 2nd order autocorrelation	0.099	0.202

[1] It is more likely to hypothesize a lag structure in the relationship between R&D expenditure and patents.
[2] Griliches (1990) writes that it would be "misleading to interpret such [patent] numbers as indicators of either the effectiveness of patenting or the efficiency of the R&D process".
[3] In response to the first point raised by Griliches, de Rassenfosse and van Pottelsberghe (2009), cross-country empirical evidence is produced in favor of patent statistics: the latter are still intensely used nowadays to measure firms' or countries' innovation performance.
[4] Indeed, if innovation is the outcome of a cumulative process, extending patent protections may be counterproductive in terms of R&D investments and consequently innovation. This result holds for high tech, semiconductors and software industries characterized by a continuous process of cumulative learning and innovations. Instead, in industries characterized by a slower innovative rhythm, the effect of patenting on R&D may be positive.
[5] However, even if firms experience sunk costs due to innovations, there are several theoretical explanations why persistence may not emerge (see, for example, Schmookler 1966).
[6] Malerba, 2005, p. 382.
[7] Table 1 in Appendix provides a detailed description of those dimensions.
[8] Other empirical papers use this kind of sectors classification in the analysis of innovation persistence. For example Malerba *et al.* (1997) say that understanding the persistence of innovation is important in terms of our conceptual view of the underlying processes which drive innovation (e.g. the Schumpeter Mark I versus Mark II). Cefis and Orsenigo

(2001) in their work state that "The issue of persistence in innovative activities is relevant in the context of the discussion about the properties of the patterns of innovative activities (SMI and SMII)". Say also Corrocher *et al.* (2007) for a study of the patterns of innovation in the ICT field using patents and patent citations.

[9] Generally, the *legal* protection of innovations ensured by patents lasts longer than the *effective patent life*, which, instead, depends on the market conditions in terms of possibility to imitate.

[10] The dataset has been realized by ISTAT; it is based on a survey of private R&D activity.

[11] In order to eliminate outliers, in table 3, such as in the empirical analysis, we dropped firms that have applied for more than 50 patents in a year.

[12] R&D expenditure includes only the *intramural* expenses made by firms.

[13] See Alexander *et al.* 1995.

[14] See Sims 1972; Holz-Eakin, Newey and Rosen 1988; Hurlin and Venet 2001; Hurlin 2005; Arellano and Bond 1991; Arellano and Bover 1995; Blundell and Bond 1998.

[15] It should be noted that there is a trade-off in the choice of lags. On the one hand, small number of lags increases the number of degrees of freedom; on the other hand, a large number of lags decreases autocorrelation.

[16] The choice to restrict the sample to firms applying for patents in at least five years has been forced to consider the trade-off between the efficiency in forecasting and the loss of the number of observations. That is, to be efficient in forecasting, we need as many past values of a variable as possible. In our case, the best we can do is to restrict the sample to firms that have applied for patents in all 7 years; but, in this way, we would lose too many observations. Thus, we restrict the panel to the firms that have applied for patents in at least 6 years. In order to be as efficient as possible and to limit the loss of observations, we decide to restrict the panel to the firms that have applied for patents in at least five years.

[17] We cannot perform unit root tests because the panel is strongly unbalanced. We run an autoregression estimation of *ln(R&D)* with FE and GMM; the coefficient of the *ln(R&D)(-1)* is about -0.04 with FE and about -0.3 with GMM. This result makes us confident with the absence of a unit root for the variable *ln(R&D)*.

[18] The definition of each variable in equation (3), its construction and their descriptive statistics are detailed in table 5 in the appendix. Table 6 shows the descriptive statistics for each variable in the SMI and SMII and table 7 illustrates the correlations among variables.

[19] See for example Brouwer and Kleinknecht 1999; Kortum and Lerner 1999; Kortum 1993.

[20] The actual patent prosecution procedures require more than three years, but we are linking R&D expenditure with patent applications; therefore the time lag between R&D expenditure with patent applications are shorter.

[21] See Arellano and Bond 1991.

[22] In the definition of the Schumpeterian patterns, in terms of the sectors of economy they include, we have followed Castellacci and Zheng (2010). When a sector included in our dataset does not appear in the Castellacci and Zheng classification, we adopted a dimensional criterion: small and medium size firms are included in SMI, large firms are included in SMII. The definition of patterns is in table 8 in appendix.

[23] The estimation in the homoskedastic case includes, step by step, all the control variables described above; in every specification we do not reject the null. We do not show the Chi^2 of the test but it is available on request.

[24] The result of the Sargan test allows us to rule out the endogeneity of *Patent*.

[25] Those estimations are available upon request. The results do not change.

[26] We have also performed every estimation including the second lag of the dependent variable and the results are the same.

[27] This coefficient represents the elasticity of the R&D expenditure (over R&D employees) with respect to a unitary variation of *Patent;* its magnitude is, in column (a), about 0.13 meaning that if *Patent* increases by 1, *R&D* increases by 0.13%.

[28] We do not show the Blundell-Bond estimation results but they are available upon request.

[29] See for example Bessen and Hunt 2007.

[30] For SMI the $Chi^2 = 2.14$ (p-value = 0.54); for SMII the $Chi^2 = 1.16$ (p-value = 0.76).