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

Anna Laura Baraldi and Claudia Cantabene and Giulio Perani

Second university of naples, Second university of naples, ISTAT

1 May 2013

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

Anna Laura Baraldi[*], Claudia Cantabene[†], Giulio Perani[‡]

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 in two directions. Firstly, it perform a Granger causality test on the theoretical presumption of a reverse patents→R&D link as an explanation of the failure of the traditional relationship. Second, assuming the reverse patents-R&D causality, we test and interpret the lag structure of such a relationship as showing the *effective patent life* which firms expect in the two Schumpeterian patterns of innovations they belong to. To 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

[*] Dipartimento di Economia, Seconda Università di Napoli, C.so Gran Priorato di Malta – 81043 Capua (Italy). +39823343340. laura.baraldi@unina2.it
† Dipartimento di Economia, Seconda Università di Napoli, C.so Gran Priorato di Malta – 81043 Capua (Italy). +393489034035. claudia.cantabene@unina2.it
[‡] Istat - DCSP/SSI/D

1. Introduction

R&D activity is the base for the production of innovation that, in its turn, drives economic growth. The innovative process is made of R&D investments, the *input* of the process, and the innovation, the *output*. The most common measure of the innovation output is *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 more 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 underlined some drawbacks in the R&D-patents traditional relationship. New theoretical approaches showed that, even if in the 1990s there was an increase in patent's 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 patent 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's direction, in terms of a weaker orientation towards patent protection of some industries (Levin *et al.* 1987) and of patent data as a "wrong" indicators of innovative activity (Griliches, 1990).

We argue that a reverse causality in the R&D-patents relationship may hold leading to the failure of the traditional R&D→patents: patent applications occur at an early point in the development process and most of the R&D expenditures occur after the application of patents is made. Only recently the research in this fields is starting 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, it becomes of utmost importance the analysis of patents→R&D (Encaoua *et al.*, 2006). The mainstream of the theoretical literature that addresses the reverse causality in the patent-R&D relationship assumes a positive correlation; empirical studies lack in corroborating this conclusion: they tend to be unclear or in disfavor of the positive correlation assumption.

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

Secondly, we ask: 1) If the reverse causality holds, are there lags between patents and R&D expenditure?; 2) How does the reverse causality relationship differ in different patterns of innovations?

Answering those questions allowed us to offer a further explanation of the innovation persistence in terms of Schumpeterian patterns of innovations that overturns the findings of the existing literature in this topic. Indeed, 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. Instead, given that 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 this light, according to the characteristics of the technological regimes (Schumpeter Mark I and Schumpeter Mark II) firms belong to, we interpret the lag structure in the patents→R&D relationship. We may expect that in sectors characterized by a high appropriability of innovations, low 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* (as the expected time until a patent product is replaced in the market) will be long (O'Donoghue et al., 1998). Therefore, they tend to enjoy the monopoly rent patent gave them and postpone the R&D activity just before their expectation that this monopoly rent will be expired. In other words, they do not persist in their R&D investment. At odds, in sectors with opposite features (the Schumpeter Mark I), firms believing in a shorter effective patent life may tend to persist in the innovative effort. Therefore, the cause of the innovation persistence on R&D we spoke above refers and depends on the *effective patent life* which is defined by the lag structure in the patents→R&D relationship.

The 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 confirmed our prediction. They showed positive and statistically significant coefficient of one year lagged dependent variable (R&D effort) and also positive and statistically significant contemporaneous coefficient of the patent applications in Schumpeter Mark I. It means that there is persistence in the R&D expenditure and such persistence is path dependent because other factors, especially the patenting activity we are interested in, affected the innovation process. Otherwise, in Schumpeter Mark II, neither the lagged dependent variable coefficient nor the patent applications coefficients (contemporaneous and until two years lagged) are significant, meaning 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 of the wideness 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 aspect 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 concludes.

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*. This overlaps two literature: the patents-R&D relationship and the innovation persistence literature.

Patents-R&D relationship literature

The traditional direction of causality in the R&D-patents relationship 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 confirmed this positive relationship (Pakes and Griliches, 1980; Griliches, 1988; Beneito, 2006). Several papers on cross-sectional data of firms, 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 or Cincera 1997). Hall et al. (1986) examine the existence of lags in the R&D→patent finding that, contrary to what would be intuitive, 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 main drawbacks in the traditional direction of causality in the R&D→patent. First, if a time-series dimension is included in the analysis, the positive correlation between R&D and

[1] It is more likely to hypothesize a lag structure in the relationship between R&D expenditure and patents.

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). Furthermore, the above correlation becomes almost absent when the analysis is at the industry level. Levin *et al.* (1987), in justifying the previous evidence, say that, in spite 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 why the estimated R&D→patent elasticity is so weak. Firstly, patent data are not a "right" indicator of innovative activity because they reflect a propensity behaviour, rather than innovation performance or research productivity.[2] Second, patent series are very random because they greatly vary in their value with most patents having low value and a few patents having very high value.[3]

Here we argue that the failure in the empirical evidence of the R&D→patents relationship when within-industry and/or time-series dimensions are taken into account may be due to a reverse causality in that relationship: patents aimed at stimulating the R&D investment; patents encourage investment in R&D and thus the production of knowledge and innovation.

The first that theoretically examined the reverse causality link between patents and R&D was Nordhaus (1969). He asserted that the extent of patent protection, enhancing the expected return on an innovation, leads to incentivize the R&D investments. Pakes (1985) suggested 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) find little evidence of a Granger-causality from R&D to patents but clear-cut evidence of a causality in the opposite direction.

Theoretically, the expectations of the signs of such a reverse causality relationship are twofold. Intuitively, the broader the patent scope or the greater the patent length is, the more the R&D effort will be (Denicolo, 1996). But, if the nature of innovations is considered (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 expenses in industries like semiconductors, software or

---

[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) produce cross-country empirical evidence 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.

biotechnology, speaking of a *patent thicket* (as a dense web of overlapping intellectual property rights).

Even if theoretical literature found justifications and conditions under which the reverse causality in the patent→R&D relationship holds, empirical works lack in confirming both a positive or negative sign (Kortum and Lerner, 1999; Hall and Ziedonis, 2001; O'Donoghue et al., 1998; Kingston, 2001; Sakakibara and Branstetter, 2001).

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 has to 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 (see Sutton 1991 or Manez Castillejo et al. 2004);[5] 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 been used to produce past 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, in Schumpeter Mark I, the "creative destruction" explains absence of persistence, whereas, in Schumpeter Mark II, the existence of significant degrees of persistence would contribute to generate processes of "creative accumulation".

Empirical studies provides mixed results about such a persistence (Geroski et al., 1997; Cefis, 2003; Roper and Hewitt-Dundas, 2008; Peters, 2009; Raymond et al., 2010; Clausen et al., 2012). Most work that have focused on patenting data, identify weak elements of persistency. On the contrary, empirical analyses based on survey data find stronger evidence of innovation persistence, but highlight that results are sensitive to the indicator chosen (Duguet and Monjon, 2004).

Once summarized the two relevant theoretical and empirical literature, we advance the hypothesis that the lag structure of the reverse relationship between patents and R&D may offer another explanation of the innovation persistence of R&D expenditure in terms of the *effective patent life*. We hypothesize that the latter is related to the different characteristics of appropriability, barriers to

[5] However, even if firms experience sunk costs due to innovations, there are several theoretical explanations that persistence may not emerge (see, for example, Schmookler 1966).

entry and dominance of large established firms of markets and industrial sectors. We base this argument on the concept of *technological regimes* in which firms operate. 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 and 2006; Malerba, 2002). We can identify the technological regime according to four dimensions: 1) Level of technological opportunities; 2) Appropriability conditions; 3) Cumulativeness conditions; 4) External sources of opportunities.[6]

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)

The patterns of innovations, originally pointed out by Schumpeter (1934 and 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. Opposite features show the *Schumpeter Mark II*; 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 displays 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

We argue that the lag structure of the patent→R&D relationship is related to the characteristics of the technological regime in which the enterprise operates. 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 gave them; they expect a longer *effective patent life* and, therefore, they may postpone the successive R&D activity just before the monopoly rent will be expired.[7] In terms of the interpretation of the lag structure of the regression of patents on R&D expenditure, we should expect negative/no contemporaneous and delayed (of at least 2-3 years, depending on the *effective patent life*) relation among them. The consequence of such a longer *effective patent life* is the absence of R&D effort persistence.

[6] Table 1 in Appendix provides a detailed description of those dimensions.
[7] 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.

In a Schumpeter Mark I pattern, on the other hand, 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 who decide to protect their innovation with patents, persist in their innovative effort. In this pattern therefore, we expect a contemporaneous relationship among patents and R&D expenditure.

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.[8] 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 in at least one year. Therefore, 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 comes from firms' balance sheets.

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.[9] More than 50% of firms do not apply for 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 apply 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 of small innovators which continuously patent a narrow number of innovations.

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

[9] In order to eliminate outliers, in table 2, such as in the empirical analysis, we dropped firms that have applied for more than 50 patents in a year.

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 the two technological patterns. However, 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

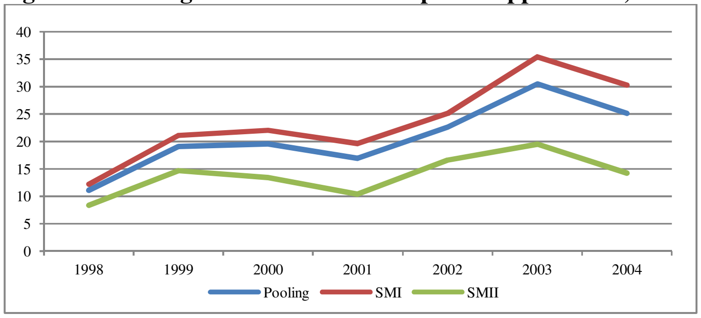
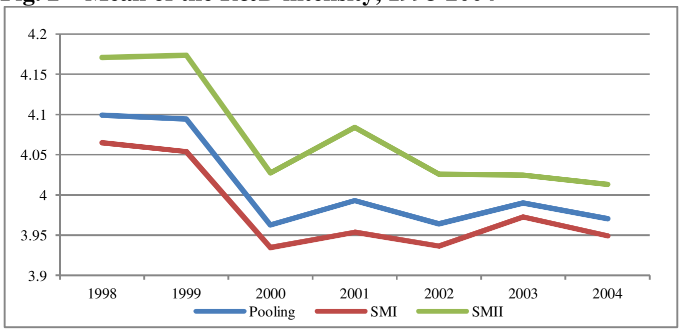


Figure 2 displays the mean, over firms, of the R&D intensity (as the ratio between R&D expenditure and employees in R&D division)[10] over the period 1998-2004, pooling and for the two Scumpeterian patterns of innovations. It is decreasing: overall, the mean value goes from about 4100 euros (per employee in R&D) in 1998 to about 3950 euros in 2004; firms in SMII have invested, on average, about 93 euros per employee more than those in SMI.

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

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

Fig. 2 – Mean of the R&D intensity, 1998-2004



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 econometric modeling of Granger causality relationship have been made. Starting from the work of Granger (1969), a lot of studies offer new approaches for testing Granger causality in panel data.[11] 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 performed a 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) just mentioned above.

For each firm *i* at time *t* we consider two variables: y_{it}, that measures the R&D intensity (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 R&D intensity that causes, in the Granger sense, patent applications or the reverse is true? 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 value 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. Here it is important the choice of lags. We checked the order of the autoregressive process of the variables of interest: both are AR(2) processes. Firstly, the estimation of model (1)[12] will allow to establish whether x_{it} Granger causes y_{it}:

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

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

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

where n is number of lags (n=2), i is 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 (ν_{it}) which represents measurement errors in the dependent variable and 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

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

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

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

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

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

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

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

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

must be rejected.

In dealing with panel data analysis, a crucial issue is the cross-sectional variation; this type of variation may be addressed with a fixed effects 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 dimension ($t<10$). 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 for which there is no causal relationship from x to y. The test statistic is defined as the cross-section average of individual Wald statistics associated with the standard Granger causality tests based on single time series. The author show that this statistic has 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 a fixed effects and a dynamic panel data model (respectively depicted as **FE** and **GMM** in table 3). The last raw 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. As concerns model (1), we may conclude that patents cause, in the Granger sense, R&D: the Wald statistics 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.[13]

To sum up, the Granger causality shows that past values of patents are important in forecasting R&D intensity, 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 Persistence estimation results

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

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

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 R&D division.[14] The former is a measure of the R&D intensity, since it captures how much a firm invests in R&D per employees in the R&D division; the latter is a standard measure of patents. γ, the auto-regression coefficient, represents our measure of persistence. We have also introduced contemporaneous and until two lags of *Patent*; we cannot

[13] We cannot perform unit root tests because of 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 an unit root for the variable *ln(R&D)*.

[14] The definition of each variable in equation (3) and its construction is detailed in table 5 in the appendix. Table 6 shows the correlations among them.

add further lags of patent applications because of the many missing value in the panel; increasing the number of lags should drastically reduce the number of observations making inference impossible to do. Equation (3) has been estimated by the Arellano-Bond technique.[15] We have performed the estimation on the two Schumpeterian patterns of innovation, Schumpeter Mark I and Schumpeter Mark II.[16] Time after time, for each pattern, we have introduce control variables in order to check the robustness of the our hypothesis. Control variables are:

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

There are not 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 driving further innovations. Moreover, it must be investigated if the early innovation is sufficient to produce long lasting consequences or whether effectively strategies and events that have been taking place along the process do affect the persistence. In other word, the process may be respectively past dependent and path dependent.

Table 8 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.[17] 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. In order to control for heteroskedasticity, every estimated equation in table 8 has robust standard errors. Each column is estimated with 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 firms belong to in order to control for an investment localization effect:[18] it is reasonable to believe that

[15] See Arellano and Bond (1991).

[16] In the definition of the Schumpeterian patterns, in terms of 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 7 in appendix.

[17] 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 available upon request.

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

firms decide to place their production in a region rather than in another to exploit knowledge spillover. The last raw 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 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. In SMII, instead, the autoregressive coefficient is not significant (but in (d) where it is negative and weakly significant).[19] Those results must be interpreted to the light of the lag structure of the patent→R&D relationship. Firms in SMI show a positive, contemporaneous and highly significant sign of patent applications coefficient.[20] Firms in SMI mostly operate in small traditional sector of economy; the "creative destruction" promotes competition among innovative firms which tend 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 make 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 8) 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, as *Patent* (we are interested in), and as all the control variables we include in the model (as shown in every column in table 8).

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 gave them. They face a longer *effective patent life* (guaranteed by the absence of competition); R&D investments are, therefore, postponed just before the expected patent rent will be expired. As just hypothesize, results in columns (b) and (d) show neither contemporary nor

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

[20] That 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 of 1, *R&D* increases of 0.13%.

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 strongly significance of the initial condition confirms that, in SMII, the present investment in R&D is affected by the early one, strengthening the presumption of a relationship between patent and R&D deferred in time.

We expect a positive sign for *ln(Sales)*: if firm's size increases, investments in R&D may increase to; it is not significant in both 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 intensity 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 intensity of 0.002% for firms in SMI and 0.001% for firms in SMII. *Patent* coefficients do not change in both SMI and SMII, as well as 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 of higher educated people. This is the reason why, in columns (g) and (h), we add the variable *Education* to control for the education level in the R&D division. A positive correlation between R&D investment and the share of graduated R&D employees is supposed, because graduates receive higher wages than less educated people. As expected its sign is positive but significant only in SMI (column g): a unitary increase in the percentage of graduated implies an increase of 0.004% in the R&D expenses per employees in 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 firm: if getting credit becomes more expensive, firm has less money to invest. In columns (i) and (l) we introduce a measure of firms debt, *Leverage*. Firms use debt as a source of financing; when the leverage increases, firm is considered more risky. *Leverage* is negative but not significant. As always, nothing changed 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 8). It is significant only in SMI with negative sign: if labor cost decreases in every division (included R&D), the resources to be invested increases everywhere. This is because a more efficient firm may have higher financial liquidity and, as a consequence, may invest more in R&D activities. In both the patterns nothing changed in the sign and significance of all other regressors.

We performed a further robustnes check that 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; results do not change.[21]

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 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 belonging to all the sectors of the economy. The Granger test results support the hypothesis that the reverse causality patents→R&D (patents occurs at an early stage on 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 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 showed 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 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, time after time, 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. In SMII, on the contrary, no regressor (but *R&D size*) becomes significant. Taking into account that, in the econometric

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

specification, we have controlled for lots of 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 value 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.

References

Aghion, P. and Howitt, P. (1992), "A model of growth through creative destruction", *Econometrica,* 60, issue 2, pp. 323–351.

Antonelli, C. (2008), "Localized technological change: Towards the economics of complexity", Routledge, London.

Antonelli C., Crespi F., Scellato G. (2012), "Inside innovation persistence: New evidence from Italian micro-data", *Structural Change and Economic Dynamics*, 23, 341-353.

Arellano, M. and Bond, S. (1991), "Some tests of specification for panel data: MonteCarlo evidence and an application to unemployment equations", *Review of Economic Studies*, 58, pp. 277–97.

Arellano, M. and Bover, O. (1995), "Another Look at Instrumental Variable Estimation of Error Component Models", *Journal of Econometrics*, 68, pp. 29–51.

Arrow, K.J., (1962), "Economic welfare and the allocation of resources for invention", *Universities-National Bureau of Economic Research Conference*, The Rate and Direction of Economic Activities: Economic and Social Factors, Princeton University Press.

Baltagi, B.H. (2005), "Econometric analysis of panel data. 3rd ed.", Hoboken, NJ: John Wiley & Sons.

Beneito, P. (2006), "The innovative performance of in-house and contracted R&D in terms of patents and utility models ", *Research Policy*, 35, pp. 502–517.

Bessen, J. and Hunt, R. (2007), An Empirical Look at Software Patents, *Journal of Economics & Management Strategy*, 16, No. 1, pp. 157–189.

Bessen, J. and Maskin, E. (2009), "Sequential Innovation, Patents, and Imitation," *The RAND Journal of Economics,* 40, issue 4, pp. 611–635.

Blundell, R. S. and Bond, S. (1998), "Initial Conditions and Moment Restrictions in Dynamic Panel data Models", *Journal of Econometrics*, 87, pp. 115–143.

Boldrin, M. and Levine, D.K. (2002), "The case against intellectual property", *American Economic Review, Papers & Proceedings*, 92, pp. 209–212.

Bottazzi, L. and Peri, G. (2003), "Innovation and spillovers in regions: Evidence from European patent data" , *European Economic Review*, 47, No. 4, pp. 687–710.

Breschi, S., Malerba, F., Orsenigo, L. (2000): 'Technological regimes and Schumpeterian patterns of innovation', *Economic Journal*, 110, 388-410.

Brouwer, E. and Kleinknecht, A. (1999), "Innovative Output and a Firm Propensity to Patent. An Exploration of CIS Micro Data" , *Research Policy*, 28, No. 6, pp. 615–624.

Castellacci, F. and Zheng, J. (2010), "Technological Regimes, Schumpeterian Patterns of Innovation and Firm Level Productivity Growth", *Industrial and Corporate Change*, Oxford University Press, 19, No. 6, pp. 1829–1865.

Cefis, E., 2003. "Is there persistence in innovative activities?" *International Journal of Industrial Organization* 21, 489–515.

Cefis, E. and Orsenigo, L. (2001), "The persistence of innovative activities; a cross country and cross-sectors comparative analysis", *Research Policy*, 30, pp. 1139–1158.

Cincera, M. (1997),"Patents, R&D and Technological Spillovers at the Firm Level: Some Evidence from Econometric Count Models for Panel Data", *Journal of Applied Econometrics*, 12, No. 3, pp. 265–280.

Clausen, T., Pohjola, M., Sapprasert K., Verspagen, B., 2012. "Innovation strategies as a source of persistent innovation". *Industrial and Corporate Change*, vol. 21, pp. 553-585.

Cohen, W. M. and R. Levin (1989), "Empirical studies of innovation and market structure", in R. Schmalensee and R.D. Willig (Eds.), *Handbook of Industrial Organization, Volume II*, North Holland.

Crepon, B., Duguet, E. and Mairesse, J. (1998), "Research, Innovation, and Productivity: An Econometric Analysis at the Firm Level, *Economics of Innovation and New Technology*, 7, No. 2, pp. 115–158.

Czarnitzki, D., Kraft, K. and Thorwarth, S. (2009), "The knowledge production of 'R and D', *Economics Letters*, 105, No. 1, pp. 141–143.

de Rassenfosse, G. and van Pottelsberghe de la Potterie, B. (2009), "A policy insight into the R&D-patent relationship", *Research Policy*, 38, No. 5, pp. 779–792.

Denicolo, V. (1996), ''Patent Races and Optimal Patent Breadth and Length'', *Journal of Industrial Economics,* 44, pp. 249–265.

Dosi, G., Marengo, L. and Pasquali, C. (2006), "How much should society fuel the greed of innovators? On the relations between appropriability, opportunities and rates of innovation", *Research Policy*, 35, No. 8, pp. 1110–1121.

Duguet, E. and Kabla, I. (1998), "Appropriation strategy and the motivations to use the patent system: An econometric analysis at the firm level in French manufacturing", *Annales d'Economie et de Statistique*, 49/50, pp. 289–327.

Duguet, E., Monjon, S., 2004. "Is innovation persistent at the firm level? An econometric examination comparing the propensity score and regression methods", Cahiers de la Maison des Sciences Economiques, Université Panthéon-Sorbonne.

Dumitrescu, E.I. and Hurlin, C. (2012). "Testing for Granger Non-causality in Heterogeneous Panels". *Economic Modelling*, 29, No. 4, pp. 1450–1460.

Encaoua, D., Guellec, D. and Martínez, C., (2006), "Patent systems for encouraging innovation: lessons from economic analysis", *Research Policy*, 35, pp. 1423–1440.

Gallini, N. (2002), "The Economics of Patents: Lessons from Recent US Patent Reform", *Journal of Economic Perspectives*, 16, No. 2, pp. 131–154.

Geroski, P., Van Reenen, J., Walters, C., 1997. "How persistently do firms innovate?" *Research Policy* 26, 33–48.

Granger, C.W.J. (1969), "Investigating causal relations by econometric models and cross-spectral methods", *Econometrica*, 37, pp. 424–38.

Griliches, Z. (1988), "Productivity Puzzles and R&D: another nonexplanation", *Journal of Economic Perspectives*, 2, issue 4, pp. 9–21.

Griliches, Z. (1990), "Patent statistics as economic indicators: a survey", *Journal of Economic Literature,* 92, pp. 630–653.

Hall, B.H. and Ziedonis, R.M. (2001), "The patent paradox revisited: an empirical study of patenting in the US semiconductor industry 1979–1995", *The Rand Journal of Economics*, 32, No. 1, pp. 101–128.

Hall, B.H., Griliches, Z. and Hausman, J.A. (1986), "Patents and R&D: is there a lag?", *International Economic Review,* 27 No. 2, pp. 265–283.

Hausman, J.A., Hall, B.H. and Griliches, Z. (1984). "Econometric Models for Count Data with an Application to the Patents-R&D Relationship", *Econometrica*, 52, No. 4, pp. 909–938.

Holtz-Eakin, D., Newey, W. and Rosen, H.S. (1988), "Estimating vector autoregressions with panel data", *Econometrica*, 56, pp. 1371–96.

Hood, M.V. III, Kidd, Q. and Morris, I.L. (2008). "Two Sides of the Same Coin? Employing Granger Causality Tests in a Time Series Cross-Section Framework", *Political Analysis*, 16, pp. 324–344.

Hsiao, C. (1986), "Analysis of panel data", Cambridge: Cambridge University Press.

Hunt, R. M. (2006), "When do more Patents reduce R&D?", *American Economic Review*, 96, issue 2, pp. 87–91.

Hurlin, C. (2005), "Testing for Granger causality in heterogeneous panel data models", *Revue Economique*, 56, pp. 1–11.

Hurlin, C. and Venet, B. (2001), "Granger causality tests in panel data models with fixed coefficients", *Working Paper Eurisco* 2001–09, University of Paris Dauphine.

Hurlin, C. and Venet, B. (2004), "Financial development and growth: A re-examination using a panel Granger test", *Working Paper*, University of Orleans, University of Paris Dauphine.

Jaffe, A. (1986), "Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits and Market Value", *American Economic Review*, 76, issue 5, pp. 984–1001.

Kingston, W. (2001), "Innovation needs patents reform", *Research Policy*, 30, 403–423.

Kortum, S. and Lerner, J. (1999), "What is behind the recent surge in patenting?", *Research Policy*, 28, pp. 1–22.

Laursen, K. and Meliciani, V. (2002), "The relative importance of international vis-ý-vis national technological spillovers for market share dynamics", *Industrial and Corporate Change*, Oxford University Press, 11, No. 4, pp. 875-894.

Lee, K. and Lim, C. (2001), "The Technological regimes, catch-up and leapfrogging: findings from the Korean industries", *Research Policy*, 30,No.3, pp. 459‐483.

Levin, R., Klevorick, A., Nelson, R. and Winter, S. (1987), "Appropriating the returns from industrial research and development", *Brookings Papers on Economic Activity*, 3, pp. 783–831.

Malerba, F. (2002), "Sectoral systems of innovation and production", *Research Policy*, 31, No. 2, pp. 247–264.

Malerba, F. (2005), "Sectoral Systems – How and why innovation differs across sectors", in: Fagerberg, J., Mowery, D., Nelson, R. (2005) The Oxford Handbook of Innovation, Chapter 14, Oxford University Press.

Malerba, F. and Orsenigo, L. (1995), "Schumpeterian patterns of innovation", *Cambridge Journal of Economics*, 19, pp. 47-65.

Malerba, F., Orsenigo, L. and Peretto, P., (1997), "Persistence of innovative activities, sectoral patterns of innovation and international technological specialisation", *The International Journal of Industrial Organisation*, 15, No. 6, pp. 801–826.

Manez Castillejo, J. A., Rochina Barrachina, M. E., Sanchis Llopis, A. and Sanchis Llopis, J. (2004). "A Dynamic Approach to the Decision to Invest in R&D: The Role of Sunk Costs." mimeo

Mowery, D. and Rosenberg, N. (1989), "Technology and The Pursuit of Economic Growth", Cambridge University Press.

Mowery, D.C. (1983), "The relationship between intrafirm and contractual forms of industrial research in American manufacturing, 1900–1940", *Explorations in Economic History*, 20, pp. 351–374.

Nelson, R.R. and Winter, S.G. (1982), *An Evolutionary Theory of Economic Change*, Harvard University Press.

Nordhaus, W. (1969), "Invention, Growth, and Welfare; A Theoretical Treatment of Technological Change", Cambridge, Mass. 1969, chapter 5.

O'Donoghue, T., Scotchmer, S. and Thisse, J., (1998), "Patent breadth, patent life and the pace of technological progress", *Journal of Economics and Management Strategy*, 7, No. 1, pp. 1–32.

Pakes, A. and Griliches, Z. (1980). "Patents and R&D at the firm level: a first look", in *Griliches, ed.,* 1984, pp. 55–72.

Pakes, A. (1985), "On Patents, R&D, and the Stock Market Rate of Return," *Journal of Political Economy* 93, pp. 390-409.

Pavitt, K. (1984), "Sectoral patterns of technical change: towards a taxonomy and a theory". *Research Policy*, 13, pp. 343–373.

Peters, B., 2009. "Persistence of innovation: stylized facts and panel data evidence". *The Journal of Technology Transfer* 34, 226–243.

Raymond, W., Mohnen, P., Palm, F., Schim van der Loeff, S., 2010. "Persistence of innovation in dutch manufacturing: Is it spurious?" *Review of Economics and Statistics* 92, 495–504.

Reichstein, T. and Salter, A. (2006), "Investigating the sources of process innovation among UK manufacturing firms", *Industrial and Corporate Change*, Oxford University Press, 15, No. 4, pp. 653– 682.

Romer, P. (1990), "Endogenous technological change", *Journal of Political Economy*, 98, No. 5, pp. S71– S101.

Roper, S., Hewitt-Dundas, N., 2008. "Innovation persistence: survey and case-study evidence". *Research Policy* 37, 149–162.

Sakakibara, M. and Branstetter, L. (2001), "Do stronger patents induce more innovation? Evidence from the 1988 Japanese patent law reforms**",** *Rand Journal of Economics*, 32, No. 1, pp. 77–100.

Schmookler, J. (1966). "Invention and Economic Growth", Cambridge, Mass.

Schumpeter, J. (1934), "The Theory of Economic Development", Harvard University Press, Cambridge, USA.

Schumpeter, J. (1943), "Capitalism, Socialism and Democracy", Harper, New York.

Shapiro, C. (2001), "Navigating the Patent Thicket: Cross Licenses, Patent Pools, and Standard-Setting," in Adam B. Jaffe, Josh Lerner, and Scott Stern, Eds., *Innovation Policy and the Economy*, Vol. I. Cambridge, MA: MIT Press.

Sims, C. (1972), "Money, Income and Causality", *American Economic Review*, 62, pp. 540–52.

Sutton, J. (1991). "Sunk Costs and Market Structure", Cambridge, Mass.

Van Ophem, H., Brouwer, E., Kleinknecht, A. and Mohnen, P. (2002), "The Mutual Relation between Patents and R&D" in A. Kleinknecht and P. Mohnen, eds., *Innovation and Firm Performance*, Hampshire and New York: Palgrave, pp. 56–70.

Winter, S. G. (1984), "Schumpeterian Competition in Alternative Technological Regimes", *Journal of Economic Behavior and Organization*, 5, pp. 137–158.

Winter, S. G. (2006), "Toward a Neo-Schumpeterian theory of the Firm", *Industrial and Corporate Change*, 15, No. 1, pp. 125-141.

Appendix

Table 1: Technological regimes dimensions

Level of technological opportunities	They 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 know
Appropriability conditions	They 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 know
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 cooperations with other agents in the innovation system. The economic environment which may offer a pool of advanced knowledge is made 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)	0.27	1.91	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 thousand of euros at constant price 2000.

Table 6: Correlations

	ln(R&D)	*Patent*	*RD Size*	*Education*	*ln(Sales)*	*Leverage*	*Labour cost*
ln(R&D)	1						
Patent	0.0342*	1					
RD 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 7: Definition of the Schumpeterian patterns

Schumpeter Mark I	mining; textiles; wearing; 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 8: Estimated results

	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
p-value 2nd 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 4. 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).