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INSIDE INNOVATION PERSISTENCE: NEW EVIDENCE FROM ITALIAN MICRO-DATA

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Inside Innovation Persistence: New Evidence from Italian Micro-data[1]

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Abstract

This paper contributes the analysis of the persistence of innovation activities, as measured by different innovation indicators and explores its past and path dependent characteristics. The study provides new insights on the role of R&D investments in innovation persistence and analyses differentiated patterns of persistence across product and process innovation, by accounting for complementarity effects between the two types of innovative behaviour. The empirical analysis is based on a sample of 451 Italian manufacturing companies observed during the years 1998-2006, and exploits both descriptive techniques such as Transition Probability Matrix and econometric methods based on dynamic probit models. Results highlight the relevance of innovation persistence. The highest level of persistence is found for R&D-based innovation activities, witnessing the actual presence of significant entry and exit barriers. Moreover, we obtain more robust evidence of persistence for product innovation than for process innovation when complementarity effects between the two types of innovation are accounted for.

KEY-WORDS: INNOVATION; PERSISTENCE; NON-ERGODIC DYNAMICS; PAST DEPENDENCE.

JEL CLASSIFICATION: O31, C23, C25, L20

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1. Introduction

The assessment of the characteristics and determinants of firm-level innovation persistence along time has clear implications for both innovation policies and the understanding of long-term industry dynamics. Relatively recent important contributions on this issue (Malerba et al. 1997) have inspired a stream of empirical studies that have provided mixed results on the actual presence and significance of persistence in innovation (Geroski et al. 1997; Geroski et al. 2001; Cefis, 2003; Duguet, 2004; Roper and Hewitt-Dundas 2008; Peters, 2009).

From a theoretical perspective the identification of the persistence of innovation relies upon three distinct and yet complementary streams of analysis implemented respectively by the economics of knowledge, the economics of organization and the economics of innovation. Let us consider them briefly in turn. According to Nelson (1959), technological knowledge as an economic good is characterized by cumulability and non-exhaustibility. Moreover, according to David (1993) knowledge is at the same time an input and output of the generation of new knowledge. These characteristics have many implications in terms of persistence. The generation of new vintages of knowledge impinges upon the existing stock that can be used as an input because of its non-exhaustibility. Firms that have been able to start generating new technological knowledge can rely upon their own output to generate new additional knowledge at lower costs with clear non-ergodic consequences. Moreover, since learning, together with research activities, is a major source of new knowledge (Arrow,1962), dynamic increasing returns are likely to characterize the performance of innovation activities: the larger is the cumulated size of innovation activities carried on and the larger are the positive effects on costs. Stiglitz (1987) has added an important dynamic element with the notion of learning to learn: firms that have started to learn about the generation of new knowledge enjoy distinctive dynamic increasing returns as they are better able to learn in the subsequent attempts to generate new knowledge.

The enquiry about the details of the knowledge generation process has identified further elements in the notion of sunk costs (Sutton, 1991). Innovation activities are characterized by relevant upfront sunk costs for the set up of research infrastructures and the required long term investments commitments needed to capitalize R&D returns (Sutton, 1991). The decision to innovate requires that substantial resources and dedicated routines are implemented. Once the decision has been taken, the opportunity costs to stop are very high because of substantial dynamic increasing returns. Sunk costs and irreversibilities in research and development activities engender major entry and exit barriers.

The economics of organization has shown that repeated interactions between the accumulation of knowledge and the creation of routines to valorise and exploit it within the same organization eventually lead to the creation of dynamic capabilities that favour the systematic reliance upon innovation as a competitive tool (Penrose, 1959; Nelson and Winter, 1982; Teece and Pisano, 1994). Finally, according to the new-schumpeterian approach, successful innovation activities have a positive impact on the conditions for follow on innovations by providing the firm with higher permanent market power, by reducing financial constraints as well as by broadening the space of available technological opportunities (Scherer, 1986). This set of arguments seems quite consistent and provides a solid base to try and implement an empirical investigation on the role of non-ergodic dynamics in innovation activities.

Most of previous empirical studies have focussed on patenting activity finding limited evidence of persistence[2]. Patents represent an important but yet partial proxy of innovation activities, they are affected by evident biases in favour of more formalised types of R&D investments and they provide very limited accountability of innovations in service sectors. Moreover, the limited availability of firm level controls in the patent based studies made it difficult to disentangle the actual determinants of observed persistence for wider groups of innovators. Other scholars have used survey data on innovation, obtaining on average sounder evidence of persistence although innovation counts do not convey sufficient information of the economic importance of the innovations analyzed. In this paper we follow the latter approach but complement it by using an Italian dataset of about 450 companies observed along the years 1998-2006. The rich structure of available data will allow us to explore in more detail three specific aspects, which we believe deserve further research efforts in the study of innovation persistence. First, we try and assess whether the introduction of innovation and the related generation of new knowledge is really shaped by non-ergodic dynamics engendered by the intrinsic characteristics of the innovation process such as cumulative forces, substantial irreversibility and positive feedbacks. In this respect we aim at the identification of true state persistence in innovation, i.e. the component of observed persistence actually attributable to the fact of having performed innovation activities in the past and not to other firm-specific factors. In so doing we try and ascertain whether contingent factors that may sustain or contrast the continual reliance of firms upon innovation persistence play a contingent role. The distinction between past dependent and path dependent non-ergodic process is important in this context: it seems in fact worth exploring to what an extent the non-ergodic persistence of innovation, once identified, be past dependent or path dependent, whether in other words, it can be shaped by contingent factors that are encountered along the dynamic process or display its effects ever since the beginning of the process with no changes in either the rate or the direction (Antonelli, 1997, 2008). Second, as the role of R&D activities in explaining innovation persistence is expected to be relevant, because of the important sunk costs associated with R&D laboratories, we try and assess in the empirical analysis the interrelationships between input and output innovation indicators. Finally, we explore whether persistence patterns vary across diverse typologies of innovation outputs (i.e. product and process innovation), by accounting for possible effects related to complementarities among different innovation activities. The appreciation of different persistence patterns for product innovation, process innovation and R&D investment can provide hints on the expected hysteretic propagation along time of the positive effects exerted by policies supporting these different types of innovations.

The rest of the paper is organised as follows. In section two we summarise the results from previous empirical studies of firm-level innovation persistence and discuss our research framework and objectives. Section three provides the description of the dataset and a detailed discussion of the analysis of persistence based on transition probability matrixes. In section four we present our econometric analysis for the estimation of true state persistence and discuss the main evidence obtained. Section five concludes and highlights the policy implications of the results.

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[2] On average the papers using patents finds little persistence in general, but strong persistence among ‘great’ innovators that account for a large proportion of patents requested.

2. Previous evidence and research objectives

2.1 Empirical studies on innovation persistence

The empirical analysis about the persistence of innovation activities is quite a recent undertaking in the economic literature. The majority of currently available evidence can be grouped into a subset of studies that build upon the analysis of large samples of patents and a subset of empirical studies that make use of data from innovation surveys repeated along time. Malerba et al. (1997) provide an important contribution in this area of investigation and tested the evidence provided by the OTAF-SPRU data base for five European countries for the period 1969-1986. The econometric evidence shows that innovation persistence is relevant and capable of shaping the patterns of innovative activities across countries and sectors. However, the majority of patent based studies identify weak elements of persistency, which exhibits strong values only in the case of heavy patentees. Cefis and Orsenigo (2001) apply a transition probability matrix to analyze the persistence of innovative activity in the years 1978-1993 for samples of some 1400 manufacturing firms in five European countries, and find weak persistence of patenting activity. More specifically their work shows that both low-innovators and great-innovators tend to remain in their classes and that much of the persistence in innovation activities seems to be determined by the 'economic' persistency of the firms themselves. This study also provides original evidence about inter-sectoral differences that confirm the importance of technology-specific factors. A subsequent study by Cefis (2003) focuses on 577 UK patenting firms in the period 1978-1991. Also in this case the transition probability matrix shows overall little persistence, characterized by a strong threshold effect. Only great innovators, in other words, have a stronger probability to keep innovating.

The result that patent activities are characterised by a limited degree of persistence is qualified in the analysis of Geroski, Van Reenen and Walters (1997) who study the innovative history of UK firms in the period 1969-1988 using the patent records and the introduction of 'major' innovations. Their results show that only in the latter case there is significant persistence in innovative activities so that only a minority of firms is persistently innovative. Finally, Latham and Le Bas (2006) provide a systematic investigation of the persistence on innovation based upon the analysis of French and US patents. Their results confirm that the persistence of innovation takes place, but only and mainly in a limited time span. Latham and Le Bas test the hypothesis that size and profitability exert a major positive effect on the spell of innovation activities: the larger are the firms and the larger their profitability and the longer the time spell over which firms are able to sustain a sequence of innovations. This work moreover expands further the investigation with the analysis of the persistence of innovation among individual inventors, as distinct from firms. The persistence of innovation is stronger among individuals than among firms. Here their results provide strong and novel evidence about the important role of 'serial inventors': creative individuals that are characterized by high levels of 'fertility' and are able to generate a persistent flow of inventions through time.

The limited ability of these studies to identify general persistence of innovative activities might be related to the specific innovation indicator used, which captures only a small part of innovative efforts and performances generated by firms. This interpretation appears to be plausible considering that empirical analyses based on survey data, which are able to take into account a large array of innovative activities pursued by firms, found stronger evidence of innovation persistence.

The first studies using innovation data to study the persistence of innovative activities were conducted by König et al. (1994) and Flaig and Stadler (1994) on a panel of manufacturing firms in West Germany. These studies provide a differentiated analysis on persistence of product and process innovation, finding evidence of state dependence in both innovative outcomes. More recently Raymond et al. (2006) who study the persistence of innovation in Dutch manufacturing firms using firm data from three Community Innovation Surveys (CIS) for the years 1994-2000, do not find true state persistence in introducing product or process innovations. However, they show that within the group of continuous innovators the market success of previous innovation positively influenced the success of subsequent innovations.

Strong persistence in product and process innovations is found by Roper and Hewitt-Dundas (2008) who use the Irish Innovative Panel in the period 1991-2002 covering 3604 plants. In this case the size and ownership of plants matters: large plants that are part of multinational companies are more able to sustain the innovation process through time than smaller ones locally owned. The persistence in the introduction of product innovations is associated with strategic variables, while the persistence in the introduction of process innovations is related to market pressure. Finally, Peters (2009) provides strong evidence in favour of persistence of innovation activities both in terms of innovations inputs, in terms of R&D activities, and innovation outputs as measured by the number of innovation introduced by German manufacturing and service firms in the years 1994-2002. The research relies upon the Manheim Innovation Panel of the ZEW and is based upon the Community Innovation Survey (CIS). The results of the empirical investigation confirm that firms experience high levels of persistence in undertaking innovation activities: almost half of the difference across firms in the propensity to innovate between previous innovators and non-innovators in the German manufacturing industry can be explained by the state dependence, i.e. whether the firm was already involved in innovation activities tat time t-1. The persistence of innovative activities is explained by the levels of: a) skills, b) support of public funding, c) financial liquidity and d) size.

Summing up, the evidence of the literature is mixed. Most works identify weak elements of persistency but do not provide a convincing consensus about its determinants and, most importantly, about the specific kind of dynamic process. In particular, the works that have used patents as a reliable indicator of the innovation suggest that the persistence is weak and exhibits strong values only in the case of heavy patentees. On the contrary, empirical analyses based on survey data found stronger evidence of innovation persistence, but highlight that the selection of the indicator to measure the extent to which the introduction of innovation has a hysteretic character is not trivial and results seem to be sensitive to the indicator chosen (Duguet and Monjon, 2004). Such heterogeneity in the empirical results suggests that further investigation of the issue is needed, in particular in order to account for the relationships between innovation input and output indicators and for the complementarities between different innovation strategies based on product and process innovation.

2.2 Research framework and objectives

In this study we adopt the empirical approach based on survey data in order to study innovation persistence at the firm level, as it provides more detailed evidence on the nature and characteristics of this dynamic process. In this respect, we claim that innovation is a highly differentiated phenomenon associated with diverse strategies of firms and specific to industry conditions (see Reichstein and Salter, 2006 and Crespi and Pianta, 2008 for extensive reviews). Hence, we expect that innovation persistence may vary, depending on the different types of innovation indicator considered (Duguet and Monjon, 2004). The use of survey data allows us to produce a differentiated analysis of persistence as captured by different input and output indicators of innovation activities, including R&D activities, product and process innovations. The joint use of such indicators makes it possible to account for the effects of complementarities between different types of innovation and for the interrelations between innovation inputs and outputs.

The rich information on firm level characteristics, deriving from the survey, enables us to improve our understanding of the actual determinants of persistence and to identify the relevance of true state persistence in innovation activities and to study the type of non-ergodic processes that characterize the innovation processes, whether it is past or path dependent. This distinction is quite relevant also from a policy viewpoint to understand the long term effects of policy interventions that help firms to initiate a persistent innovation process that is not (less) likely to be disturbed or compromised by contingent factor that affect this dynamics.

The generation of technological knowledge is indeed an activity characterized by significant indivisibility and learning (Stiglitz, 1987) and the production of new knowledge deriving from R&D efforts is affected by substantial sunk costs (Máñez et al., 2009). These peculiarities of the knowledge production process determine the emergence of both barriers to entry and exit. While it is hard for companies to enter in a strategic competition based on R&D activities, corporations that have invested in R&D are more likely to keep investing simply because the incremental costs of the internal facilities designed to introduce innovations are relatively low (Arrow, 1974: Klepper, 1996). For these reasons we expect to find evidence of persistence in particular for R&D based innovation activities.

With respect to the differentiated analysis of persistence for product and process innovation we expect that this might be influenced by complementarities between the two types of innovation activities at the firm level[3]. In particular, it appears to be relevant to distinguish between repeated process innovation aimed at continuously increasing the efficiency of production processes and process innovations that may follow the introduction of new products as they can induce necessary changes in the production processes (Abernathy and Utterback, 1975).

In the case of product innovation it should be stressed that the strategic routines associated with product innovation activities are typical of monopolistic competition markets, where the continuous introduction of product innovations allows firms to enjoy substantial extra-profits. In this context we expect that product innovation shows a high degree of persistence since the introduction of new product is embedded in firms' routines related to product portfolio strategies. This hypothesis is consistent with the model elaborated by Gruber (1992) about the role of sequential product innovations in maintaining the leadership in markets characterized by vertical differentiation. For this reasons we expect that major persistence should characterise the introduction of new products even after accounting for complementarity effects.

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[3] We acknowledge the useful suggestion by an anonymous referee on this point.

3. The empirical analysis

3.1 Data description

The analysis is based on a dataset derived from the questionnaire surveys developed originally by the investment bank Mediocredito Centrale (MCC, now Unicredit), regarding a representative sample of Italian manufacturing firms with more than 11 employees. The original MCC database comes from three different questionnaire waves, each of them collecting contemporary and retrospective (previous three years) data from samples of more than four thousand firms. In order to obtain a balanced panel dataset for our study, we merged three waves (covering years from 1998 to 2006). We cleaned the dataset by eliminating outliers and cases of M&As, ending up with a balanced panel of 451 manufacturing firms observed three times over a 9-year period. The questionnaires collect information on different aspects of innovation activities providing evidence on the different types of innovations introduced by firms and on their R&D efforts, along with data on a set of firm-level characteristics. This allows us to test the relevance of innovation persistence both in terms of input and output measures of innovation. In the following Table 1 we report the sectoral composition of the sample. In 2002, the central year of the panel, the companies included in the sample had an average number of employees equal to 191.47, 47.51% of them reported positive R&D expenditures and about 76% of them were exporters (Table 2).

In our analysis we opted for using a balanced panel dataset because such data structure is required for the econometric analysis based on dynamic probit models. For sake of clarity and comparability the transition probability matrixes presented in section 3.3 are based on the same balanced panel. However, in Annex A we also show the results for a set of transition probability matrixes based on an unbalanced panel dataset with an higher number of observations. As will be discussed results on persistence indicators remain unchanged.

Each questionnaire wave reports data on innovation activities (e.g. having performed product innovation or process innovation, having done R&D investments) on a three-year basis. Only the data on R&D expenditures are also available on a yearly basis. In order to keep homogeneity across the different indicators in the analysis of transition probabilities we will use the three-year based indicators. However, in Annex A we also report the results on persistence for the R&D expenditures indicator computed on a yearly basis.

[Insert Table 1 here]

[Insert Table 2 here]

Consistently with the theoretical discussion, in our modelling framework we follow two complementary approaches. In the first part of the analysis, we investigate the presence of firm-level persistence by means of transition probability matrixes (TPM). In the second part, we explore firm-level innovation persistence by means of discrete choice panel data models based on the recent estimator proposed by Wooldridge (2005) and applied by Peters (2008). While the initial TPM approach is expected to provide only summary evidence on the persistence of firms' innovative activities along time, the panel data analysis aims at identifying the actual impact of past firms' innovation performance after controlling for relevant contingent factors. In the following Table 3 we report the definition of the innovation variables that will be used in the empirical.

[Insert Table 3 here]

3.2 Descriptive analysis based on Transition Probability Matrixes

In this section we provide descriptive evidence on the extent of innovation persistence, using transition probability matrixes and different innovation indicators. This allows us to investigate how the persistence in innovative behaviours is reflected by different indicators, that measure different aspects of innovation activities by firms. Following Cefis (2003) it is possible to model the sequence of innovation and non-innovation states as a stochastic process approximated by a two-state Markov chain with transition probabilities:

$$P[X_t = i \mid X_{t-1} = j] = \begin{bmatrix} p, (1-p) \\ (1-q), q \end{bmatrix}$$

Each term of the (2X2) TPM will be the conditional probability, or the probability of moving from state j to state i[4]. TPM results can be analyzed in two different perspectives. The first explores the horizontal distribution of probabilities, the second concentrates the attention on the diagonal analysis, providing us with information on the overall rate of persistence. The first approach has received lesser attention so far and yet it helps to quantify the magnitude of entry barriers (southern part) and exit barriers (northern part) to innovation. In this way it is possible to derive an overall picture on what we can label, by drawing from well established IO literature, firms barriers to mobility in the innovation process (Caves and Porter, 1979). More specifically, in the case of a 2-dimensional matrix, the diagonal and horizontal analyses enable to identify the following situations (Roper and Dundas, 2008):

i) Transient innovation: if the sum of the lead diagonal terms is less than 1 there is no evidence of persistence.
ii) Weak innovation persistence: if the sum of the main diagonal terms is more than 1 but some of these terms are lower than 1/n (in this case 0.5).
iii) Strong innovation persistence, if the sum of the main diagonal terms is more than 1 and all the main diagonal terms are larger than 1/n (in this case 0.5).

Moreover: a) the higher are barriers to exit the larger is the upper horizontal difference i.e. the difference between the probability of performing further innovation activities and the

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[4] Let P_{ij} and $\hat{P}_{ij}$ denote the population and sample probabilities of a transition of a company from the status i to the status j. This transition process can also be seen as the outcome of a binomial distribution. Hence, standard errors of the estimated transition probabilities can be calculated as a binomial standard deviation: $\sqrt{P_{ij} * (1 - P_{ij}) / N}$ where N equals the number of companies in status i. As N increases $\hat{P}_{ij}$ tends to P_{ij} . In the matrixes that will be presented in our analysis the binomial process has just two possible outcomes, hence the estimated standard error is the same for the elements of each row in the 2X2 matrix.

probability of exiting innovation activities; b) the higher are barriers to entry the larger is the lower horizontal difference i.e. the difference between the probability of maintaining null innovative efforts and the probability of entering in the innovation process.

The following Table 4 reports the TPMs for the different indicators of innovative activities: i) a general innovation output indicator that takes into account the development of new products and new processes; ii) an indicator of product innovation; iii) an indicator of process innovation and iv) an indicator associated with formal R&D investments. The transition probability matrixes for the three innovation output indicators have been computed for the two subsets of R&D investing companies and non-R&D investing companies.

[Insert Table 4 here]

As already mentioned, there is evidence of strong innovation persistence, if the sum of the main diagonal terms is more than 1 and all the main diagonal terms are larger than 0.5. This always applies to our data with the exception of the case of the general innovation output indicator. Such a result represents a first indication of the presence of some form of inter-temporal stability in innovation effort that has to be qualified by looking in more details at our empirical findings. First of all, the sum of the main diagonal terms allows us to rank the different innovation indicators by the overall magnitude of persistence in firms' behaviours. The indicator reflecting the choice between investing or not investing in R&D activities appears to be the one associated with the highest global inter-temporal stability (1.30). A similar pattern can be identified for firms introducing product innovation (1.26). On the other hand, the overall magnitude of persistence decreases when looking at the general innovation output indicator (1.17) and at the indicator associated with the introduction of new production processes (1.16). A further indication of the different magnitude of state dependence measured by alternative indicators emerges if we look at the difference in probabilities of being innovative in period T for firm that have engaged or not in innovative activities in period T-1. While the probability of investing in R&D in period t is 31 percentage points (hereafter: PP) higher for R&D performers in period t-1 than for non-R&D performers in t-1 and the probability to introduce product innovation in t is 26 PP higher for product innovators in t-1 than for non-product innovators, the probability of introducing any form of innovation in period t is 17 PP greater for innovators at t-1 than for non-innovators in t-1. Moreover, the probability to introduce new processes in period t is "only" 16 PP higher for process innovators in t-1 than for non-process innovators at t-1. The horizontal analysis provides interesting evidence about the absolute relevance of barriers to entry and barriers to exit the innovation activity. In Table 4 we see that barriers to exit the innovation process are highest in the case of Innovation Output: when firms have included some form of innovation in their routines they are likely to keep innovating. At the other extreme we find the case of Process Innovations where the horizontal difference between cells yields the lowest level of 0.14, suggesting that firms rely on the introduction of process innovations occasionally. The introduction of Product Innovations ranks second in the levels of the upper horizontal persistence with a score of 0.38. Firms that have experienced the introduction of product innovations are keen to keep in relying on the introduction of new products as a stable component of their market strategies.

Barriers to entry in the innovation process are clearly very strong when R&D activities are considered[5]. The lower horizontal difference for R&D activities is in fact the largest (0.32) among the four innovation indicators that we have considered. These results suggest that it is rather difficult to activate unprecedented R&D based innovation efforts (the transition probability in this case is 0.34). Here the presence of relevant sunk costs and barriers to entry related to R&D investment seem to matter in locking-out firms from R&D activities, with 2 over 3 non-R&D performers in period t-1 still being non-R&D performers at time t.

The evidence analyzed so far provides a first indication on the existence of intrinsic differences in persistence patterns characterising different indicators. In particular, the role of R&D activities in innovation persistence and the appreciation of differences in the stability test for product and process innovations are issues that need further investigation.

With respect to the first aspect Table 4 proposes for each innovation output indicators the TPMs for the sub-samples of R&D and non-R&D performers. Results are straightforward and indicate that the degree of innovation persistence for all indicators is strongly influenced by the presence of R&D activities. Non R&D based innovation activities appear to be more sporadic as evidenced by the probability of exiting innovation, which is systematically greater for the group of non-R&D performers in all the considered indicators. On the contrary, R&D investments reduce barriers to entry in innovation, with a transition probability from a negative to a positive status always higher for the sub-sample of R&D performers. Such results reflect the fact that the creation of a R&D laboratory is characterized by major sunk costs implying a long term commitment. The activity of a R&D laboratory requires that the generation of technological knowledge and the introduction of technological innovations become a systematic component of the firm strategy and innovation turns out to be a stable element of the routines of the firms.

The issue related to the identification of differences in persistence for product and process innovations has to be better qualified by taking into account possible effects of complementarity between the two types of innovation outcome. In order to highlight the potential relevance of this aspect, the following Table 5 reports the incidence in the dataset of firm-period occurrence of different types of innovations. As it is shown, in about 30% of cases we jointly observe product and process innovation, suggesting complementarity effects might influence our results.

[Insert Table 5 here]

We therefore proceed with our analysis of persistence for product and process innovation by splitting our sample between firms that at t-1 jointly introduced (or not) the two types of innovation. In particular, calculations reported in upper part of Table 6 allow us to analyse persistence in product innovation for companies having introduced process innovation at t-1, while the lower TPM report probability values related to product innovation for firms which have not engaged in process innovation at t-1. The TPMs in Table 7 can be read symmetrically. The joint analysis of the two tables highlights that complementarity affects the detected persistence in particular for process innovation. In this case in fact the probability of continuously introducing new processes is quite stronger for the sub-group of firms having realized also product innovation with respect to the sub-group of only process innovators. On the contrary, in the case of persistence in product innovation do not emerge indications of systematic differences between the two sub-

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[5] Table A2 in Annex A reports the results on persistence for the R&D expenditures indicator computed on a yearly basis. The results indicate that the three-year based indicator does not lead to an upward bias in the measure of R&D persistence.

groups. We interpret this result as a signal that process innovations might be characterized by lower levels of long term stability. This evidence can be interpreted as a consequence of the tight relationship between the introduction of process innovations and the purchase of capital goods by upstream manufacturers. Downstream firms introduce process innovations when major investments take place and the lay-out of the production process is changed. At this time the interactions with upstream producers are very strong. When the flow of investments is lower and is characterized by cumulability rather than substitution, the rate of introduction of process innovations slows down. On the opposite product innovations become a stable component of the strategy of firms that rely on the flows of new products as a long-term component of their competitive strategies. In this way product innovations feed the oligopolistic rivalry in product markets.

The persistence of process innovations seems characterized by elements of path-dependence. Investment decisions affect the actual persistence of introduction of process innovations. Persistence in product innovations seems stronger and closer to past dependence: once firms have been able to introduce new products the likelihood that they keep introducing product innovations in the future is higher.

[Insert Table 6,7 here]

We conclude this section by looking at two potential relevant factors that might influence the persistence in innovation activities that is the size of companies and the type of sector of economic activity in which they operate. The differentiated analysis by the two size classes provided in Table 8 suggests that the probability of persistently innovating increases with firm size independently from the indicator adopted. This implies that barriers to exit increase with firms' dimension. Symmetrically we find that, for all the innovation indicators considered, barriers to entry are negatively correlated with the size of firms. The exam of the persistence of innovation activities and the relevance of barriers to entry and to exit the different kinds of innovations distributed across the Pavitt taxonomy is also telling (Table 9). Persistent innovation activities are highest in the science-based industries and lowest in supplier dominated industries.

[Insert Table 8 here]

[Insert Table 9 here]

The analysis conducted so far provides strong preliminary indications for state dependence in innovative activities, in particular those related to R&D investment and to the introduction of new products in markets. Moreover, the persistence analysis conducted for the sub-samples of R&D investors and non-R&D performers has highlighted the existence of relevant barriers to entry related to R&D investments that contribute substantially in determining the overall rate of state dependency observed for all the output innovation indicators.

It should be clear that such findings provide only a preliminary evidence of the relevance of persistence in innovation, suggesting the presence of some form of inter-temporal stability in innovation efforts. However, they do not provide, yet, a sound indication on how much the observed persistence can be identified as true persistence driven only by previous states. The observed persistence can be clearly influenced by other factors, and the evidence provided in Table 8 and 9 offers precise hints in this direction. Results suggest in fact that innovation persistence, independently from the specific indicator used, is indeed influenced by factors such as size or the technological characteristics of industries. In particular the size of the companies turns to be positively associated with a higher persistence and a similar pattern can be identified for firms operating in science-based sectors. The econometric analysis in the next section aims specifically at controlling for those factors that can affect the observed persistence in order to isolate true state persistence effects.

4. Econometric analysis

4.1 Econometric models

In order to analyze the persistence of innovation along the analyzed periods we have adopted different time varying dummy variables that equal one in period t if a company declares different typologies of innovations. We apply a dynamic discrete choice models in which such variables are regressed against their past realization and a set of appropriate controls. In order to account for sectoral innovation specificities we include in the model four sectoral dummies based on the reclassification of industries according to the Pavitt taxonomy.

Observed persistence may be due to true state dependence or permanent unobserved heterogeneity across the analysed companies. By a theoretical perspective, if the source of persistence is due to permanent unobserved heterogeneity, individuals show higher propensity to take a decision, but there is no effect of previous choices on current utility and past experience has no behavioural effect (Heckman, 1981).

In our specific context, we can assume that expected drivers of true state persistence include the existence of dynamic increasing return to innovation effort, the sunk costs related R&D previously incurred by a company, and the intrinsic cumulativity of the stock of knowledge that feeds the innovation process. On the other side, the source of unobserved serially correlated characteristics that make firms more or less likely to innovate relate to risk attitude of entrepreneurs and other idiosyncratic features. By controlling for a set of observable firm specific dimensions and using a dynamic panel model we expect to obtain a clearer view of the actual persistence.

The baseline specification for a dynamic discrete response model is the following, where y_{it} is our innovation indicator:

$$y_{it}^{*} = \gamma y_{it-1} + \beta x_{it} + u_i + \varepsilon_{it} \qquad \text{Eq. (1)}$$

The estimation of the above model requires an important assumption on the initial observations y_{i0} and their relationship with u_i, the unobserved individual effects. In fact, if the start of the analysed process does not coincide with the start of the available observations, y_{i0} cannot be treated as exogenous and its correlation with the error term would give raise to biased estimates of the autoregressive parameter γ, that represents our measure of persistence. Two different approaches can be adopted for handling such initial condition problem: Heckman (1981) suggests to specifying the distribution of y_{i0} conditional on u_i and x_i; alternatively, Wooldridge (2005) proposes to specify the distribution of u_i conditional on y_{i0} and x_i. In our empirical analysis we have applied the latter approach. In particular, we follow the methodology applied by Peters (2009) which offers a simplification of the Wooldridge method, by using the first realisation of the innovation indicators (y_{i0}) and the time-averaged covariates as predictors of the individual effect, according to the following relationship:

$$u_i = \alpha_0 + \alpha_1 y_{i0} + \alpha_2 \bar{x}_i + c_i \qquad \text{Eq. (2)}$$

Where:

$$\bar{x}_i = T^{-1} \sum_{t=1}^{T} x_{it} \qquad \text{Eq. (3)}$$

Under the assumption that the error term c_i is distributed as $N(0,\sigma_c^2)$ and that $c_i \perp (y_{i0}, \bar{x}_i)$ we obtain that:

$$u_i \mid y_{i0}, \bar{x}_i \approx N(\alpha_0 + \alpha_1 y_{i0} + \alpha_2 \bar{x}_i \ , \sigma_c^2] \qquad \text{Eq. (4)}$$

and the dynamic probit model can be rewritten according to the following specification:

$$P(y_{it} = 1 \mid y_{i0}, \ldots, y_{it-1}, x_i, \bar{x}_i, c_i) = \phi(\gamma y_{it-1} + \beta x_{it} + \alpha_0 + \alpha_1 y_{i0} + \alpha_2 \bar{x}_i \ + c_i) \qquad \text{Eq. (5)}$$

This methodology has the advantage of being less restrictive on exogeneity assumptions with respect to the Heckman's one. The method amounts to estimating a dynamic random effect probit model in which regressors include a dummy representing the initial realization of the dependent variable and the time average of those covariates that are expected to be correlated to the individual effect.

The econometric analysis is based on the following structure. We start by analysing the extent of innovation persistence for each of the indicators used in the previous transition probability matrixes. Estimates are based on a baseline model specification in which we control for size, industry, the amount of fixed investments and export activities. We then add controls for the impact of R&D expenditures. All specifications are estimated both with a standard random effect dynamic probit approach and with the Wooldridge (2005) approach in which we control for endogeneity.

The estimated level of persistence along time in product or process innovation can be affected by the presence of complementarity at the firm level among these two typologies of innovations. Hence, in order to further explore the patterns of persistence we have also performed a set of model specifications in which the persistence in one indicator (e.g. product innovation) is estimated conditional on the firm not having performed at time t-1 the other type of innovation (e.g. process innovation).

4.2 *Results*

Table 10 shows the results for different specifications of the persistence model regarding the general innovation output indicator. We report both the simple random effect dynamic probit estimates and models estimated with the Wooldridge approach. Results for the Innovation Output variable indicate that, after controlling for different firm specific factors[6], the probability of observing an innovation in period t is still positively affected by the previous realization of the considered innovation variable

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[6] We have tested other regression models with additional control variables (including firms ownership structure) that turned-out to be not statistically significant and not affecting the significance of the coefficients associated with the past realizations of innovation variables.

(models I and II in Table 10). However, when including controls for R&D expenditures and the endogeneity we can no longer find evidence of true state persistence (model IV). This seems to reflect the results emerged from the analysis of transition probability matrix computed for the innovation output indicator. In particular, we can argue that the innovation persistence measured by this aggregated innovation output indicator is substantially associated with the group of R&D performers within the innovators' population.

In order to investigate in detail the actual patterns of persistence we moved to the analysis of specific indicators. Results are reported in Table 11. In this case we find evidence in favour of significant persistence in both product and process innovation (models I to VIII), which turns out to be robust to the inclusion of R&D among covariates and to the adoption of a modelling approach that endogenise the initial observation.

It is interesting to note that the R&D indicator shows the higher persistence coefficient in the baseline specification (model IX). However, once we control for endogeneity we observe a relevant reduction in the estimated coefficient, meaning that a large share of variance is actually captured by the initial observation. The case of R&D activities is the only one in which the initial condition is significant. The case for past dependence here seems very clear and the performance of R&D activities appear to act as an effective discriminant factor in separating dynamic processes.

[Insert Table 10 here]

[Insert Table 11 here]

The results obtained for the lagged dependent variables in Table 11 (models I to VIII) seem to indicate a higher inter-temporal elasticity of product innovation with respect to process innovation. However, coefficient's standard errors do not allow stating the presence of significant differences across pairs of models with usual confidence levels. As evidenced by the descriptive analysis, we claim that estimated results on individual indicators might be influenced by the presence of complementarities at the firm level between different typologies of innovations.

In Table 12 we report the results for the analysis of persistence respectively in product and process innovation, conditional on a firm not having performed at time t-1 also the other type of innovation. Such model specification is meant to depurate our estimates from complementarity effects, which may determine an upward bias in the estimated persistence. Note that we might have opted for introducing jointly among covariates the lagged indicators of product and process innovation. However, this would cause problems of multicollinearity in our estimates.

[Insert Table 12 here]

The results are interesting because they highlight differentiated patterns of persistence among product and process innovation, confirming the evidence provided by the descriptive analysis. While we still observe a significant dependence of the product innovation variable on its past realization, an analogous pattern cannot be identified for the process innovation indicator. This result appears to have relevant implications. Firstly, when we look at the dynamics of process innovation for those firms that do not carry out also product innovation persistence disappears suggesting that the sole process innovation is more sporadic than product innovation. Part of the persistence evidenced in models VI to VIII of Table 11 is due to the fact that firms that introduce new products tend to perform process innovation in the following periods in order to improve the production efficiency (Abernathy and Utterback, 1975; Utterback, 1996). Secondly, the estimates for model III of Table 12 confirm the robustness of the result of persistence for product innovation. Moreover, the joint significance of R&D variables as well as of the past realization of product innovation suggests that part of state dependence is not strictly related to sunk costs associated with R&D activities, but is attributable to the fact that product innovations become a stable component of firms' routines that rely on the flows of new products as a long term component of their competitive strategies.

Finally, in the analysis of persistence the introduction of a number of different control variables allows not only to assess the robustness of the relationships identified between past and current realization of the dependent variables, but also provides us with interesting hints for the analysis of the determinants of the observed dynamic process. In particular, the significant effect of relevant variables is most important as it confirms the path dependent character of the non-ergodic persistence.

The levels of R&D intensity, as measured by the two indicators R&D expenditures per employee and the share of internal R&D over total, as well as the level of fixed capital investment enhance the probability of subsequent innovation outcomes. Such result confirms the idea that investment activities is partly associated with the presence of sunk costs that might motivate the continuous undertaking of innovation activities. Moreover, the results suggest that the variable SIZE has a positive effect with the exception of the model estimated on R&D activities. However, the estimated coefficient associated with SIZE looses its significance when we control for endogeneity. A similar pattern can be observed for the variable on firms' export propensity whose coefficient is sufficiently robust only for the case of the R&D indicator. Finally, the dummies associated with Pavitt classes are always jointly significant, confirming the descriptive evidence that highlighted differentiated patterns in the persistence of innovative activities among different groups of economic sectors.

5. Conclusions

In this paper we have investigated the degree of firm level persistence of different typologies of innovation activities, using both transition probability matrixes and a set of dynamic probit models. The study complements previous empirical evidence mostly based on patent based indicators. In particular, our research adds to previous literature as it offers new insights on the identification of true state persistence and detailed evidence on the role of R&D investments in innovation persistence. Moreover, the analysis of different indicators of innovation output allowed us to appreciate differentiated patterns of persistence across product and process innovation, by accounting for complementarity effects between the two types of innovative behaviour.

The analysis of TPMs highlighted the presence of innovation persistence in the observed sample of companies, suggesting differentiated patterns of persistence across different types of innovative activities. In particular, the descriptive results showed higher innovation persistence in the group of R&D performers and suggested the importance of taking into account complementarity effects in the analysis of state dependence in product and process innovation. The descriptive evidence on the relevance of innovation persistence is confirmed by the econometric results, which turn out to be robust to the introduction of a set of firm-specific controls, including size, sectoral affiliation, exporting, investments in fixed assets, intensity of R&D expenditures and after accounting for firms unobservable heterogeneity. However, the levels of persistence as captured by the inter-temporal elasticity between the innovation indicators show appreciable variations according to the typology of innovation considered. The higher level of persistence is found for the R&D based innovation activities, witnessing the actual presence of significant entry and exit barriers. Furthermore, after controlling for complementarity effects between the two types of innovation we obtain more robust evidence of persistence for product innovation than for process innovation.

The variety of forms of innovation persistence found in our analysis sheds some light upon the specific form of non-ergodic dynamics at work. Non-ergodic dynamics in fact can be either past dependent or path dependent: in the latter case the effects of hysteresis are qualified and shaped by current events. In the former the process is shaped by the initial conditions only. Results, as indicated by the empirical literature and focused by our approach, confirm the path dependent character of innovation activities, as opposed to pure deterministic past-dependence. Moreover, we found robust evidence of true state persistence for the cases of R&D activities and product innovation, in which the routinized behaviour characterizing firms' competitive strategies plays a relevant role in explaining innovation persistence.

Our results have important implications for the selection of the targets and the tools of innovation policies. The provision of funding and assistance to the performance of R&D activities in fact is likely to display persistent effects in the long term. In the same way the public support for product innovation is likely to change the routines of receiving firms by placing the search for new products as a stable component of their business strategies. On the contrary, the provision of fiscal subsidies to the adoption of process innovations is likely to exert its effects in the short terms and it is less likely to have a propagation effect in subsequent periods.

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TABLES

Table 1 Sectoral composition of the sample

NACE Rev. 1 Sectors	Number of firms	%
FOOD PRODUCTS AND BEVERAGES	33	7.32
TEXTILES	32	7.1
WEARING APPAREL, DRESSING AND DYING OF FUR	13	2.88
LEATHER, LEATHER PRODUCTS AND FOOTWEAR	19	4.21
WOOD AND PRODUCTS OF WOOD AND CORK	11	2.44
PULP, PAPER AND PAPER PRODUCTS	16	3.55
PRINTING AND PUBLISHING	9	2
COKE, REFINED PETROLEUM PRODUCTS AND NUCLEAR FUEL	2	0.44
CHEMICALS AND CHEMICAL PRODUCTS	19	4.21
RUBBER AND PLASTICS PRODUCTS	23	5.1
OTHER NON-METALLIC MINERAL PRODUCTS	29	6.43
BASIC METALS	24	5.32
FABRICATED METAL PRODUCTS, except machinery and equipment	63	13.97
MACHINERY AND EQUIPMENT, N.E.C.	84	18.63
OFFICE, ACCOUNTING AND COMPUTING MACHINERY	1	0.22
ELECTRICAL MACHINERY AND APPARATUS, NEC	17	3.77
RADIO, TELEVISION AND COMMUNICATION EQUIPMENT	8	1.77
MEDICAL, PRECISION AND OPTICAL INSTRUMENTS	14	3.1
MOTOR VEHICLES, TRAILERS AND SEMI-TRAILERS	3	0.67
OTHER TRANSPORT EQUIPMENT	6	1.33
MANUFACTURING NEC	25	5.54
TOTAL	451	100

Table 2 Summary statistics for the sample for year 2002.

	Mean	median	st dev	5%	95%
Number of employees	191.47	46	651.43	10	5725
Number of employees in R&D	7.83	1	29.83	0	225
Age	29.45	26	17.8	5	130
Turnover (MEuro)	51.11	7.94	234.93	1.9	141.01
Fixed capital investments (Meuro)	1.86	0.21	7.91	0	7
Export	76.24%				
Positive R&D expenditures	47.51%				

Table 3 Definition of variables.

INPDT	Dummy variable that equals one if the company performs product innovation
INPCS	Dummy variable that equals one if the company performs process innovation
INRD	Dummy variable that equals one if the company declares positive R&D expenditures
INNOV OUTPUT	Dummy variable that equals one if the company performs either product or process innovation
SIZE	Log of the number of employees
EXPORT	Dummy variable that equals one if the company exports
LOG INV	Log of the fixed assets investments performed by the company
R&D/EMPL	Ratio of the average R&D expenditures to the number of employees
SH.INT.R&D	Ratio of the cost of internally performed R&D to the total R&D expenditures

Table 4 Transition probabilities between period T-1 and T along years 1998-2006. Transition matrixes computed for the full sample and the two subsamples of R&D investors and non R&D investors. Standard errors in parentheses.

INNOVATON OUTPUT

T T-1	Yes	No
Yes	0.759 (0.0174)	0.241 (0.0174)
No	0.593 (0.0285)	0.407 (0.0285)

R&D Investors

	Yes	No
Yes	0.805 (0.0177)	0.195 (0.0177)
No	0.740 (0.0339)	0.260 (0.0339)

Non R&D Investors

	Yes	No
Yes	0.538 (0.0484)	0.462 (0.0484)
No	0.576 (0.0433)	0.424 (0.0433)

PRODUCT INNOVATION

T T-1	Yes	No
Yes	0.692 (0.0235)	0.308 (0.0235)
No	0.436 (0.0218)	0.564 (0.0218)

R&D Investors		
T T-1	Yes	No
Yes	0.721 (0.0242)	0.279 (0.0242)
No	(0.540) (0.0278)	0.460 (0.0278)

	Non R&D Investors	
T T-1	Yes	No
Yes	0.452 (0.0768)	0.548 (0.0768)
No	0.263 (0.0316)	0.737 (0.0316)

PROCESS INNOVATION

T T-1	Yes	No
Yes	0.570 (0.0244)	0.430 (0.0244)
No	0.413 (0.0222)	0.587 (0.0222)

R&D Investors		
T T-1	Yes	No
Yes	0.606 (0.0267)	0.394 0.0267
No	0.477 (0.0275)	0.523 0.0275

		Non R&D Investors
T T-1	Yes	No
Yes	0.408 (0.0564)	0.592 (0.0564)
No	0.281 (0.0355)	0.719 (0.0355)

R&D INVESTMENT

T T-1	Yes	No
Yes	0.646 (0.0229)	0.354 (0.0229)
No	0.340 (0.0219)	0.660 (0.0219)

Table 5 Incidence of different combinations of innovation activities in the same period.

Product Innovation Process Innovation	Yes	No
Yes	30.67%	16.33%
No	16.70%	36.29%

Table 6 Analysis of persistence in product innovation conditional on process innovation

Sample restricted to companies doing process innovation in period t-1		
T T-1	Yes	No
Yes	0.695 (0.0298)	0.305 (0.0298)
No	0.442 (0.0379)	0.558 (0.0379)
Sample restricted to companies not doing process innovation in period t-1		
T T-1	Yes	No
Yes	0.687 (0.0382)	0.313 (0.0382)
No	0.433 (0.0267)	0.567 (0.0267)

Table 7 Analysis of process innovation persistence conditional on product innovation

<table>
<tr><td colspan="3">Sample restricted to companies doing product innovation in period t-1</td></tr>
<tr><td>T
T-1</td><td>Yes</td><td>No</td></tr>
<tr><td>Yes</td><td>0.632
(0.0312)</td><td>0.368
(0.0312)</td></tr>
<tr><td>No</td><td>0.449
(0.0410)</td><td>0.551
(0.0410)</td></tr>
<tr><td colspan="3">Sample restricted to companies not doing product innovation in period t-1</td></tr>
<tr><td>T
T-1</td><td>Yes</td><td>No</td></tr>
<tr><td>Yes</td><td>0.483
(0.0381)</td><td>0.517
(0.0381)</td></tr>
<tr><td>No</td><td>0.398
(0.0264)</td><td>0.602
(0.0264)</td></tr>
</table>

Table 8 Transition probabilities between period T-1 and T along years 1998-2006 by size classes (50 employees threshold).

PRODUCT INNOVATION

Less than 50 employees

T T-1	Yes	No
Yes	0.647 (0.0386)	0.353 (0.0386)
No	0.371 (0.0272)	0.629 (0.0272)

More than 50 employees

T T-1	Yes	No
Yes	0.721 (0.0294)	0.279 (0.0294)
No	0.5373 (0.0352)	0.4627 (0.0352)

PROCESS INNOVATION

Less than 50 employees

T T-1	Yes	No
Yes	0.4201 (0.0380)	0.5799 (0.0380)
No	0.3579 (0.0277)	0.6421 (0.0277)

More than 50 employees

T T-1	Yes	No
Yes	0.6736 (0.0301)	0.3264 (0.0301)
No	0.5 (0.0361)	0.5 (0.0361)

R&D INVESTMENT

Less than 50 employees

T T-1	Yes	No
Yes	0.5488 (0.0389)	0.4512 (0.0389)
No	0.3092 (0.0265)	0.6908 (0.0265)

More than 50 employees

T T-1	Yes	No
Yes	0.7048 (0.0277)	0.2952 (0.0277)
No	0.3988 (0.0384)	0.6012 (0.0384)

Table 9 Transition probabilities between period T and T-1 along years 1998-2006 by Pavitt Classes for product innovation, process innovation and R&D investments.

	PRODUCT INNOVATION				PROCESS INNOVATION		
	T T-1	Yes	No		T T-1	Yes	No
Supplier dominated	Yes	0.653 (0.044	0.347 0.044)		Yes	0.521 (0.039)	0.479 (0.039)
	No	0.382 (0.029	0.618 0.029)		No	0.426 (0.033)	0.574 (0.033)
	T T-1	Yes	No		T T-1	Yes	No
Scale intensive	Yes	0.696 (0.055)	0.304 (0.055)		Yes	0.561 (0.055)	0.439 (0.055)
	No	0.362 (0.047)	0.638 (0.047)		No	0.402 (0.051)	0.598 (0.051)
	T T-1	Yes	No		T T-1	Yes	No
Specialised suppliers	Yes	0.703 (0.035)	0.297 (0.035)		Yes	0.616 (0.040)	0.384 (0.040)
	No	0.575 (0.045)	0.425 (0.045)		No	0.630 (0.040)	0.370 (0.040)
	T T-1	Yes	No		T T-1	Yes	No
Science based	Yes	0.778 (0.080)	0.222 (0.080)		Yes	0.688 (0.116)	0.313 (0.116)
	No	0.737 (0.101)	0.263 (0.101)		No	0.567 (0.090)	0.433 (0.090)

R&D INVESTMENTS

	T T-1	Yes	No
Supplier dominated	Yes	0.587 (0.044)	0.413 (0.044)
	No	0.314 (0.029)	0.686 (0.029)

	T T-1	Yes	No
Scale intensive	Yes	0.600 (0.057)	0.400 (0.057)
	No	0.283 (0.045)	0.717 (0.045)

	T T-1	Yes	No
Specialised suppliers	Yes	0.684 (0.033)	0.316 (0.033)
	No	0.448 (0.051)	0.552 (0.051)

	T T-1	Yes	No
Science based	Yes	0.737 (0.071)	0.263 (0.071)
	No	0.625 (0.171)	0.375 (0.171)

Table 10 Dynamic probit model with random effects on innovation persistence. Dependent variable INNOVATION OUTPUT. Baseline model (I); models accounting for R&D (III, IV). Models II and IV control for endogeneity of the lagged dependent variable.

Model	I	II	III	IV
Dependent Variable	INN OUTPUT	INN OUTPUT	INN OUTPUT	INN OUTPUT
INN OUTPUT (t-1)	0.300***	0.236*	0.220**	0.155
	(0.098)	(0.121)	(0.103)	(0.129)
SIZE	0.102**	0.037	0.122***	0.087
	(0.041)	(0.127)	(0.043)	(0.135)
EXPORT	0.370***	0.016	0.270**	-0.071
	(0.103)	(0.203)	(0.107)	(0.209)
LOG INV.	0.029***	0.026***	0.019**	0.017*
	(0.008)	(0.009)	(0.009)	(0.010)
R&D/EMP.			0.563***	0.577**
			(0.216)	(0.242)
SH. INT. R&D			0.795***	0.645***
			(0.145)	(0.174)
INN OUTPUT (t0)		0.058		-0.026
		(0.119)		(0.125)
AVG. SIZE		0.043		0.004
		(0.138)		(0.147)
AVG.R&D/EMP.				-0.131
				(0.280)
AVG. EXPORT		0.482**		0.424*
		(0.240)		(0.249)
AVG.SH.INT.R&D				0.455*
				(0.269)
AVG INV.		0.015		0.012
		(0.019)		(0.020)
Dummy Pavitt	Yes	Yes	Yes	Yes
Constant	-0.626***	-0.735***	-0.786***	-0.828***
	(0.162)	(0.174)	(0.172)	(0.185)
Wald Chi-sq.	86.97***	91,61***	139.49***	145.89***
Obs.	902	902	902	902
N. of Firms	451	451	451	451

Table 11 Dynamic probit model with random effects on innovation persistence. Dependent variables: product innovation (INPDT), process innovation (INPCS), R&D activities (R&D). Baseline models (I,V,IX)); model accounting for intensity of R&D investment (III,VII). Models that account for endogeneity of the lagged dependent variable (IV, VIII,X).

Model	I	II	III	IV	V	VI	VII	VIII	IX	X
Dependent Variable	**INPDT**	**INPDT**	**INPDT**	**INPDT**	**INPCS**	**INPCS**	**INPCS**	**INPCS**	**R&D**	**R&D**
INPDT (t-1)	0.476***	0.452***	0.410***	0.419***						
	(0.094)	(0.117)	(0.096)	(0.122)						
INPCS (t-1)					0.310***	0.251**	0.289***	0.218**		
					(0.088)	(0.107)	(0.089)	(0.109)		
R&D (t-1)									0.543***	0.238*
									(0.096)	(0.131)
SIZE	0.094**	0.145	0.108***	0.172	0.140***	0.088	0.148***	0.101	0.026	-0.150
	(0.038)	(0.125)	(0.039)	(0.134)	(0.038)	(0.117)	(0.038)	(0.121)	(0.038)	(0.122)
EXPORT	0.509***	0.071	0.435***	0.002	0.208**	0.025	0.145	-0.017	0.556***	0.498**
	(0.103)	(0.195)	(0.106)	(0.203)	(0.101)	(0.196)	(0.102)	(0.197)	(0.107)	(0.201)
LOG INV	0.012	0.011	-0.002	-0.004	0.022***	0.014*	0.013*	0.007	0.033***	0.030***
	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.009)
R&D /EMPL			0.323**	0.168			0.076	0.104		
			(0.134)	(0.172)			(0.099)	(0.139)		
SH. INT. R&D			0.707***	0.727***			0.462***	0.350**		
			(0.120)	(0.151)			(0.113)	(0.144)		
INPDT (0)		-0.010		-0.120						
		(0.122)		(0.126)						

Model	I	II	III	IV	V	VI	VII	VIII	IX	X
INPCS (0)						0.068		0.056		
						(0.107)		(0.108)		
R&D (0)										0.454***
										(0.134)
AVG SIZE		-0.072		-0.092		0.004		-0.008		0.178
		(0.135)		(0.144)		(0.127)		(0.131)		(0.133)
AVG EXPORT		0.621***		0.591**		0.235		0.176		0.037
		(0.235)		(0.245)		(0.233)		(0.236)		(0.243)
AVG LOG INV		0.005		0.010		0.037**		0.035*		0.005
		(0.018)		(0.019)		(0.018)		(0.018)		(0.019)
AVG R&D /EMPL				0.402				-0.120		
				(0.283)				(0.215)		
AVG SH. INT. R&D				-0.025				0.331		
				(0.250)				(0.232)		
Dummy Pavitt	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-1.027***	-1.103***	-1.177***	-1.265***	-1.048***	-1.165***	-1.118***	-1.212***	-1.150***	-1.197***
	(0.156)	(0.168)	(0.163)	(0.176)	(0.153)	(0.165)	(0.155)	(0.168)	(0.158)	(0.173)
Wald Chi-sq.	113.95***	119.42***	165.51***	171.41***	66.17***	71.56***	87.15***	99.35***	141.58***	154.34***
Observations	902	902	902	902	902	902	902	902	902	902
Num Firms	451	451	451	451	451	451	451	451	451	451

Table 12 Dynamic probit model with random effects on innovation persistence. Dependent variables: product innovation (INPDT), process innovation (INPCS). Models I to III estimate the probability that $INPDT_t$=1 as a function of INPDT $_{t-1}$ and a set of covariates, conditional on $INPCS_{t-1}$=0. Models IV to VI estimate the probability that $INPCS_t$=1 as a function of INPCS $_{t-1}$ and a set of covariates, conditional on $INPDT_{t-1}$=0. Baseline models (I,IV); models accounting for R&D (II,V); models that account for endogeneity of the lagged dependent variable (III, VI).

Model	I	II	III	IV	V	VI
Dependent Variable	**INPDT**	**INPDT**	**INPDT**	**INPCS**	**INPCS**	**INPCS**
INPDT (t-1)	0.433***	0.350**	0.470**			
	(0.140)	(0.156)	(0.182)			
INPCS (t-1)				0.142	0.137	0.137
				(0.121)	(0.123)	(0.156)
SIZE	0.091	0.105	0.263	0.193***	0.195***	0.231
	(0.055)	(0.064)	(0.200)	(0.051)	(0.051)	(0.168)
EXPORT	0.594***	0.504***	-0.024	0.058	-0.028	-0.056
	(0.138)	(0.154)	(0.274)	(0.124)	(0.127)	(0.266)
LOG INV	0.009	-0.004	-0.004	0.015	0.010	0.004
	(0.011)	(0.012)	(0.013)	(0.010)	(0.010)	(0.012)
R&D /EMPL		0.647**	0.579**		0.327*	0.717***
		(0.255)	(0.278)		(0.186)	(0.269)
SH. INT. R&D		0.888***	0.897***		0.479***	0.157
		(0.193)	(0.224)		(0.158)	(0.215)
INPDT (0)			-0.372*			
			(0.195)			
INPCS (0)						-0.049
						(0.154)
AVG SIZE			-0.174			-0.076
			(0.216)			(0.183)
AVG EXPORT			0.722**			0.012
			(0.327)			(0.307)

Model	**I**	**II**	**III**	**IV**	**V**	**VI**
AVG LOG INV			0.004			0.023
			(0.026)			(0.023)
AVG R&D /EMPL			0.132			-1.044**
			(0.362)			(0.508)
AVG SH. INT. R&D			0.045			0.795**
			(0.355)			(0.358)
Dummy Pavitt	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-1.030***	-1.279***	-1.375***	-1.082***	-1.171***	-1.166***
	(0.213)	(0.270)	(0.250)	(0.199)	(0.203)	(0.218)
Wald Chi-sq.	61.97***	70.42***	112.43***	29.75***	49.97***	56.94***
Observations	491	491	491	516	516	516

ANNEX A

Table A1 - Transition probabilities between period T-1 and T along years 1998-2006. Transition probability matrixes are computed using the pooled sample of firms observed in survey waves I-II (1049 companies) and II-III (2097 companies).

T T-1	**INNOVATION OUTPUT**	
	R&D Investors	
	Yes	No
Yes	0.814 (0.0110)	0.186 (0.0110)
No	0.735 (0.0202)	0.265 (0.0202)
	Non R&D Investors	
	Yes	**No**
Yes	0.524 (0.0201)	0.476 (0.0201)
No	0.394 (0.0172)	0.606 (0.0172)

T T-1	**PRODUCT INNOVATION**	
	Yes	**No**
Yes	0.633 (0.0149)	0.367 (0.0149)
No	0.378 (0.0106)	0.622 (0.0106)

T T-1	**PROCESS INNOVATION**	
	Yes	**No**
Yes	0.532 (0.0138)	0.468 (0.0138)
No	0.335 (0.0106)	0.665 (0.0106)

T T-1	**R&D INVESTMENT**	
	Yes	**No**
Yes	0.612 (0.0140)	0.388 (0.0140)
No	0.265 (0.0100)	0.735 (0.0100)

Table A2 – Transition probabilities for R&D Investment between period T-1 and T along years 1998-2006. The transition probability matrix is computed on an yearly basis for the balanced sample.

T T-1	**Yes**	**No**
Yes	0.82 (0.012)	0.18 (0.012)
No	0.11 (0.009)	0.89 (0.009)