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THE PERSISTENCE OF INNOVATION: THE ITALIAN EVIDENCE

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THE PERSISTENCE OF INNOVATION: THE ITALIAN EVIDENCE[1]

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ABSTRACT. This paper contributes the analysis of the persistence of innovation activities, as measured by total factor productivity (TFP) and explores its path dependent characteristics. The empirical analysis of firm level TFP for a sample of 7020 Italian manufacturing companies observed during the years1996-2005 confirms that firms that have been able to improve the general efficiency of their production process at time t are likely to keep innovating in the following periods of time, more than firms that never innovated before. The empirical analysis is based on both transition probability matrixes and on dynamic discrete choice panel data models. The evidence suggests that innovation persistence is path dependent, as opposed to past dependent. The dynamics of the process in fact is typically non-ergodic, yet it is not exclusively determined by its but is shaped by a number of complementary and contingent factors origins that affect locally the sequence of the hysteretic effects of the early state dependence.

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

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THE PERSISTENCE OF INNOVATION: THE ITALIAN EVIDENCE

1.INTRODUCTION

According to the conventional economic wisdom, innovation is an exogenous random shock that like manna falls from heaven. The economics of innovation impinges upon the view that innovation is the deliberate and intentional result of the capability of firms to generate new knowledge and to apply it to new products, new process, new organizational methods, new combinations of inputs and new markets.

The generation of new knowledge and the introduction of innovations are the result of a creative and localized reaction that takes place when firms face unexpected events in both factor and product markets. In order to face such events firms mobilize the internal stocks of knowledge accumulated by means of learning processes. The chances that the reaction of the firm actually leads to the successful introduction of innovations, relies upon the access to the knowledge available in the surroundings. In other words, the reaction of firms to unexpected events becomes actually creative when both the competence accumulated by means of internal learning processes and a number of external conditions in terms of knowledge communication apply.

The persistence of the innovative activity takes place when A) the competitive pressure pushes firms to react by means of more than traditional price-quantities adjustments but to try and change their technologies. Firms can actually react creatively to face unexpected events by means of the introduction of new technologies and new organizational methods and introduce successful innovations when two conditions are fulfilled: B) they are actually able to learn to learn and C) the external context qualifies the intentional action of firms and provides the access to complementary and indispensable inputs in terms of external knowledge. In such cases the dynamic process is likely to be characterized by significant hysteretic, non-ergodic features.

This dynamics in fact is characterized by recursive feedbacks. The introduction of new technologies and new organizations methods affects the systems on two counts as it engenders further waves of unexpected events and Schumpeterian rivalry, and, at the same time, makes available new knowledge spillovers. Hence the introduction of innovations can be considered as the persistent and emerging property of an economic system where the interdependence between the dynamics of learning, internal to firms, and the evolving structure of interactions among firms that determines the actual amount of external knowledge available within the system, exert path dependent, rather than past dependent, effects. 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 the localized context of action. In the former the process is shaped by the initial conditions only (Antonelli, 2008).

With this approach in the background, the aim of this work is twofold. First, we contribute the literature on the persistence of innovation with a traditional and yet novel measure of innovative activity. Second, we qualify the characteristics of the persistence and explore the determinants. In so doing we relate the literature on the persistence of innovation to the notion of path dependence.

More specifically, the aim of the paper is to confirm and strengthen the evidence about the persistency of innovation activities and to qualify the form of non-ergodic dynamics at work with the identification of its path dependent characteristics. The rest of the paper is structured as it follows. Section 2 reviews the literature on the matter. Section 3 outlines the hypotheses and the research design of this study. Section 4 presents the econometric evidence. The conclusions summarize the main results.

2. PRIOR RESEARCH

The empirical analysis about the persistence of innovation activities is quite a recent undertaking in the economic literature. In the special issue of the *International Journal of Industrial Organization* dedicated to the economics of path dependence, Malerba, Orsenigo and Petretto (1997) pave the way to this new area of investigation.

They test the hypothesis that innovation is not a purely random shock, but rather the outcome of a cumulative process that is both internal and external to firms. Knowledge indivisibility and more specifically knowledge cumulability account for the internal forces that explain the persistence of innovative activities. The market structure and the type of competition among firms push firms to rely systematically upon innovation as a competitive tool. Innovation is more persistent when firms are engaged in oligopolistic rivalry. The empirical investigation relies upon patents as an indicator of innovative activity. The model tested the evidence provided by the OTAF-SPRU data base for five European countries: Germany, France, UK, Italy and Sweden for the period 1969-1986 for 33 technological categories. The econometric evidence confirms that the innovative activity is persistent. The rest of the paper however does not investigate the determinants and the features of the persistency but rather analysis its effects. It shows in fact that the persistence of the innovative activity plays an important role in explaining the concentration of technological activity, that is the share of patents delivered to the firms, the stability of the ranking of innovators and their innovative intensity.

Geroski, Van Reenen and Walters (1997) study the innovative history of UK firms in the period 1969-1988 using the patent records and the introduction of ‘major’ innovations. The empirical analysis is based upon the estimate of a proportional hazard function and consists in the empirical investigation of the innovative spells. Their results are simply summarized as it follows: ”success only follows really major success, and then for only a limited period of time”. A minority of firms is persistently innovative.

Cefis and Orsenigo (2001) provide disaggregate evidence about the persistence of innovative activities as measured by patent statistics. This study tests a transition probability matrix to analize the persistence of innovative activity in the years 1978-1993 for samples of some 1400 manufacturing firms in each country, respectively in Germany, Italy, Japan, US and France. The results show that innovative activities are characterized by a weak persistency. More specifically both low-innovators and great-innovators tend to remain in their classes. Much of the persistence in innovation activities however seems to be determined by the ‘economic’ persistency of the firms themselves. This study provides original evidence about inter-sectoral differences that confirm the importance of technology-specific factors.

Cefis (2003) explores the innovative persistence of a group of 577 UK patenting firms in the period 1978-1991. The study investigates the probability that firms that have applied for a patent at time t-1 have a stronger probability to apply for a patent at time t+1 than firms that did not applied for a patent in the prior period. According to her results the transition probability matrix shows little persistence in general and it is characterized by a strong threshold effect. Only great innovators, in other words, have a stronger probability to keep innovating.

Cefis and Ciccarelli (2005) contribute the literature on the persistence of innovation exploring the persistence of the effects of innovation rather then the persistence of innovation per se and its causes. This paper investigates the effects of innovative activity on profitability using a panel of 267 UK firms in the period 1988-1992. The innovativity of firms is measured by means of patent statistics. The econometric model tests with a Bayesian approach and classical estimation methods the hypothesis that past innovations exert a short and long term positive effect upon the profits of firms. The results of the Bayesian approach confirm that the impact of innovation on profits is cumulative and long lasting. This work provides a tangential contribution to the identification of persistence of innovation, as it confirms that because past innovations have a long lasting effect on profitability, innovation at time t can be positively influenced by past innovation via the greater availability of financial resources.

The approach by Alfranca, Rama and von Tunzelmann (2002) is quite original in this context. They study the persistence of innovation in a specific sector with a focus on a well-identified group of firms. They analyze 16,698 patents granted in the United States from 1977 to 1994 to 103 global firms in the food and beverage industry. They test whether patent time series are trend stationary or difference stationary to detect how large the autoregressive parameter is and how enduring is the impact of past innovation on current ones in these companies. Their results show that the 17 years patent series are not consistent with the random walk model. The evidence confirms that global firms, both of very large and smaller size, in this industry, exhibit a stable pattern of technological accumulation in which “success breeds success”.

Latham and Le Bas (2006) make an important contribution to the field with 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.

The work coordinated by Latham and Le Bas 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. Here the results of Latham and Le Bas provide a new and important specification to the hypothesis that the distribution of creativity be characterized by the working of the well-known Pareto Law: not only a few patents account for a large share of the value, but a few innovators are 'responsible' for a large share of the important innovations (Scherer and Harhoff, 2000).

A stronger evidence about the persistence of innovative activities is provided by a new flow of empirical investigations based upon innovation counts.

Peters (2008) confirms the strong 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). A firm is defined as an innovator when it exhibits positive innovation expenditures and has introduced a new product and a new process. 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. To identify the drivers of persistence Peters uses a dynamic random effect probit model. The persistence of innovative activities is explained by the levels of: a) skills, support of public funding, c) financial liquidity and d) size.

Raymond, Mohnen, Palm, Schim Van Der Loeff (2006) study the persistence of innovation in Dutch manufacturing using firm data from three Community Innovation Surveys (CIS), in the years 1994-1996, 1996-1998, and 1998-2000. The number of innovations that each firm claims to have introduced in each period of observation is the unit of analysis. They test the hypothesis of persistence with a maximum likelihood dynamic panel data tobit model accounting for individual effects and handling the initial conditions problem. Their findings suggest that there is no evidence of true persistence in achieving technological product or process innovations. At each point in time however the shares of sales stemming from innovative products, introduced in the past have a –small- effect on the current shares of sales of innovative products.

Roper and Hewitt-Dundas (2008) use innovation survey data and show that in the case of 3604 plants covered by the Irish Innovative Panel in the period 1991-2002 both product and process innovations are strongly persistent. Their empirical evidence shows that innovating plants have a stronger probability to introduced further innovations than non-innovating ones. 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 to strategic variables, while the persistence in the introduction of process innovations is associated to market pressure.

In conclusion, 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 important, about the specific kind of dynamic process. The selection of the indicator to measure the extent to which the introduction of innovation has a hysteretic character is not trivial. Prior investigations have used either patent statistics or innovation counts to measure innovation. The results seem to be sensitive to the indicator (Duguet and Monjon, 2004).

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 patentors. The papers that rely upon innovation counts instead find much a stronger persistence.

In order to provide additional empirical evidence upon the persistence of innovation we shall try and measure the extent to which innovation is persistent at the firm level by means of the measure of total factor productivity growth. We shall retain, instead, the methodology implemented by many authors such as Cefis and Orsenigo (2003), Cefis (2005) and Peters (2008) consisting in the analysis of the distribution of transition probabilities between states, i.e. the state of innovator and the state of innovator. This approach seems reliable because it enables to better explore the probabilities of persistence rather than deterministic approaches based upon standard analysis of serial correlation along time either in levels or growth rates. The analysis of transition probabilities moreover seems appropriate for comparative purposes.

3. HYPOTHESES AND RESEARCH DESIGN

The introduction of innovation and the related generation of new knowledge is shaped by cumulative forces, substantial irreversibility and positive feedbacks. Hence innovation is expected to be a persistent process reinforced by external feedbacks and contingent factors that may sustain or contrast the continual reliance of firms upon innovation.

The hypothesis that innovation is persistent is based upon the following main arguments:

A) The generation of technological knowledge is an activity characterized by significant indivisibility and learning. Knowledge indivisibility and learning to learn exerts strong cumulative effects (Stiglitz, 1987).

B) The generation of new knowledge and the introduction of innovations is the result of the creation, within corporations, of new functional routines and of research and development laboratories and of the structure of the communication networks that qualify the access to the external knowledge. Both are characterized by substantial sunk costs. Hence corporations that have innovated once are more likely to keep innovating simply because the incremental costs of the internal facilities designed to introduce innovations are very low (Arrow, 1974).

C) The well-known dynamics of the Matthew effect is likely to apply not only to scientists but also to firms for at least two classes of reasons. First, it seems plausible that innovating firms are able to pay higher wages and hence to attract more creative and talented employees. Second, innovating firms are likely to interact with innovative suppliers and innovative customers and hence to feed more fertile and productive user-producers interactions. For both reasons firms able to introduce an innovation at time t are more likely to keep innovating at time t+1 than firms that have not introduced any innovation (David, 1994).

D) Innovative firms are better able to accumulate knowledge and to elaborate business strategies to improve its exploitation. Innovative firms are better able to implement internal markets where innovative undertakings can match financial liquidity made available by previous innovations. The repeated interaction between the accumulation of knowledge, the creation of routines to valorize and exploit it eventually leads to the creation of dynamic capabilities that favor the systematic reliance upon innovation as a competitive tool (Penrose, 1959; Teece and Pisano, 1994).

In order to study the persistence of innovation we rely upon a classic indicator such as the total factor productivity. We assume in fact that innovation has much a broader scope than indicators such as the generation and introduction of science-based new technologies that patent statistics tend to emphasize, or the specific introduction of new products and processes, measured by innovation counts.

Innovation consists, more generally, in the systematic capability to generate new knowledge and to apply it to the broad array of activities that firms carry on. So far our notion of innovation is much broader and retains a strong Schumpeterian flavor as it includes the introduction of new products and new processes as well as the introduction of changes in the organization, in the mix of inputs and in the product and factor markets into which firms operate. Hence we assume that total factor productivity is better able to capture the general increase in the efficiency of the firm that is engendered by the command of technological, organizational and commercial knowledge.

The generation of new knowledge is the result of the integration of learning processes, both internal and external to each firm, formal research and development activities and the acquisition, both in the market place and by means of networking activities, and eventual recombination of external knowledge. Different forms of knowledge, i.e. scientific, commercial, technological, organizational, contribute the generation of new knowledge an different kinds of activities are required: learning, networking, absorption, research, scientific outsourcing. Each of these activities is complementary and indispensable as much as each form of knowledge is a necessary input into the generation of new knowledge.

Total factor productivity measures seem better able to catch the results of the localized generation and application of new knowledge to the economic activity.

The empirical assessment of the actual persistence of innovation within firms opens a new set of questions about the characters of such a dynamic process. The identification of a persistence leads us to unfold the problem of the identification of the specific characters of the dynamic processes where historic time matters and hence the qualification of the non-ergodic process at work process where time matters.

Early innovators have a stronger chance of introducing further innovations and this higher probability to keep innovating through time would be independent from other contingent and specific conditions. Clearly in this case an event that takes place at an early point in time is expected to exert – for ever- a long-term effect. Such an effect is not likely to be modified by other subsequent events. In the latter case, instead, contingent conditions exert an effect and the persistence may be increased and strengthened or weakened (David, 1985 and 1997).

Clearly our hypothesis here is that the probability to introduce an innovation at time t+1 is conditional both to the introduction of an innovation at time t and to the effects of contingent forces that exert their effect locally so as to affect the sequence of state dependency. In other words we argue that innovation activities are characterized by strong non-ergodic effects that are typically path dependent.

Our two hypotheses lead to a two-step research design that can be summarized as it follows. In a first step we focus the analysis upon the identification of the persistence of the innovative activity as measured by TPM (Transtion Probability Matrix) computed using variations in the levels of total factor productivity.

In the second step we concentrate the analysis upon the determinants of the persistence as we want to qualify the type of non-ergodicity at work, as well as the role of non-observable heterogeneity.

It seems important to stress, also in terms of policy implications, that when observed persistence is driven only by idiosyncratic factors, policy interventions are likely to be much less effective than in the case of 'true' state dependence. In the latter case in fact we can assume that once a firm has been induced to innovate the likelihood that it will keep innovating is enhanced.

Our main argument here is that a number of contingent and localized conditions exert a significant effect upon the process. The persistence of the innovative activity, hence, is path dependent and it is not past dependent. The path dependence is the result of the effects of contingent and localized factors that arise through time (David, 1997 and 2007).

Contingent factors can be both internal and external. Internal factors have been already considered. Financial liquidity provides the means to fund innovative undertakings and reduce the well-known problems of the access to external financial sources. Wages measure the quality of internal human capital and hence the likelihood that firms can rely upon learning and learning to learn as a source of competence to implement the internal stocks of knowledge so as to generate additional knowledge and to introduce eventual innovations.

The large and systematic evidence about the working of the Gibrat Law suggests that the size of firms cannot exert a positive effect upon the persistence of innovative activity: hence we expect that the size of firms is not relevant (Geroski, 1994).

External factors have not yet been properly considered. Two external factors play a major role:

A) The access to the local pools of knowledge generated by the spillover of the innovative activity of other firms co-localized in the proximity of each firm provides a key contribution to the persistence of innovative activities. Such effects are typically inter-industrial: knowledge generated in an industry may be useful in other activities (Jacobs, 1969). Hence we expect that the levels of total factor productivity of firms co-localized in the same region, irrespective of the industrial sector, favor the persistence of innovation. The higher the levels of total factor productivity of all the firms that are co-localized and the higher we expect to be the innovation persistence.

B) the levels of the innovative activity of firms within the same industry and hence active in the same product markets, measure the extent to which the typical Schumpeterian rivalry based upon the introduction of innovation is at work. The higher are the levels of total factory productivity of rival firms and the stronger is the competitive pressure. The Schumpeterian rivalry pushes firms to innovate in order to survive. Hence we expect that the higher is the efficiency of the rivals within the same industry and the larger is the likelihood that each firms relies upon the introduction of innovation as a competitive tool and hence the stronger is the persistence of innovation. These hypotheses are 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.

External factors add to internal ones and shape the context into which the persistence of innovation takes place. The external conditions, namely the quality of local knowledge pools and the strength of the Schumpeterian rivalry, together with the internal conditions, that is the actual levels of dynamic capabilities, as proxied by the levels of wages and internal liquidity, exert a specific and localized effect upon the non-ergodic dynamics of sequential introduction of innovations. According to their effects the persistence can be more or less past dependent. It becomes fully path dependent when the contingent and localized factors do exert a significant effect upon the sequence of innovations.

4. THE EMPIRICAL EVIDENCE

4.1. THE DATA

Our analysis is based on an original dataset containing balance sheet accounting data for a sample of Italian manufacturing firms. The dataset includes complete financial accounting data for a large sample of manufacturing companies, observed along years 1996-2005. The data have been extracted from the AIDA database provided by Bureau Van Dick, which reports accounting information for public and private Italian firms with a turnover larger than 0.5 millions of Euros. We started by a random draw of companies with at least 15 employees at the end of fiscal year 1995. The companies included in the analysis have been founded before year 1995, they are registered in a manufacturing sector according to the Italian ATECO classification, and they are still active by the end of year 2005. In order to drop outliers due to possible errors in the data source, we computed a set of financial ratios and yearly growth rates of employees, sales and fixed capital stock. After a manual checking we eventually dropped 45 companies which showed unreasonable data. We ended up with a balanced panel of 7020 companies. All financial data have been deflated according to a sectoral two-digit deflator using year 2000 basic prices. In annex 1 we report the sectoral composition of the dataset.

4.2 TOTAL FACTOR PRODUCTIVITY AS A MEASURE OF INNOVATIVITY

We investigate the persistence in innovation activity, as measured by firm level total factor productivity TFP. The rates of increase of TFP are good measures of the degree of innovativeness of the firms. This is especially true with respect to the Italian system where, although the levels of formalized R&D activities and patenting are low, much innovation is based upon informal research activities, tacit knowledge and learning. Hence, we assume that the bottom line increase of efficiency at the firm level is the ultimate indicator of the wide array of interrelated effects of the introduction of changes in products, processes, markets, organization and inputs (Parisi, Schiantarelli, Sembenelli, 2006).

In order to compute firm-level TFP we have firstly estimated a set of Cobb-Douglas production functions with constant returns to scale for each industry included in the sample, so to obtain the correct levels of output elasticity of labor and capital. After the assignment of each firm to an industry we have computed TFP for company i in year t according to the following expression:

$$TFP_{i,t} = \frac{Q_{i,t}}{L_{i,t}^{\beta} K_{i,t}^{1-\beta}} \tag{3}$$

Where:

$Q_{i,t}$:deflated value added

$L_{i,t}$:average number of employees

$K_{i,t}$:fixed capital stock.

Fixed capital stock has been computed using a perpetual inventory technique according to which the first year accounting data, i.e. year 1996 in our case, are used as actual replacement values. The subsequent yearly values of fixed capital are computed using a depreciation parameter δ, assumed equal to 6.5%, and adding deflated yearly investments. The investment parameter ($I_{i,t,}$) has been computed as the yearly variation in net fixed capital in companies' balance sheets plus yearly amortizations. Hence, the time series of fixed capital is defined as follows:

$$K_{i,t} = (1-\delta)K_{i,t-1} + I_{i,t} / p_t \tag{2}$$

In order to identify the parameter β at industry level to compute equation 1, we have estimated for each industry the following equation:

$$Log\left(\frac{Q_{i,t}}{K_{i,t}}\right) = \beta \times Log\frac{L_{i,t}}{K_{i,t}} + \alpha_i + \alpha_t + \varepsilon_{i,t} \qquad (3)$$

We have used a fixed effect estimator (Blundell and Bond, 2000; Olley and Pakes, 1996), where α_i is a firm specific effect and α_t is a time specific effect.

4.3 TESTING INNOVATION PERSISTENCE

Consistently with the theoretical discussion, in our modeling 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 recently applied by Peters (2008). Finally, in order to check for robustness of the results we also rely upon a model based on the theoretical approach suggested by Heckman (1981) and implemented by Stewart (2007). While the initial TPM approach is expected to provide only summary evidence on the persistence of firm level TFP levels along time, the panel data analysis aims both at identifying the impact of contingent factors on the persistence of innovation and at disentangling the share of persistence due to firm-specific unobservable idiosyncratic features. In the following tables we report the definition of the variables that will be used in the different empirical analyses.

Table 1 – Definition of variables. All reported variables are time varying. Financial variables are deflated using year 2000 basic prices.

Variable	Definition
TFP	Log(TFP)
SIZE	Log(Total Assets) computed with perpetual inventory method
WAGE	Labour costs/number of employees
PCM	Price-cost-margin
INNO	Dummy = 1 in year t if TFP_t-TFP_{t-2}>0
REG	Average TFP of all companies in the same region of firm i excluding the contribution of firm i
SECT	Average TFP of all companies in the same sector of firm i, excluding the contribution of firm i

4.3.1. **THE ANALYSIS OF THE TRANSITION PROBABILITY MATRIX**

In this section we provide summary evidence on the extent of innovation persistence, using transition probability matrixes. We assume that a positive growth rate of TFP over a two year time window indicates the presence of some form of innovation. 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:

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

The corresponding AR(1) process for the stochastic variable Xt then is the following:

$$X_t = (1-q) + \rho X_{t-1} + \upsilon_t$$

where $\rho = p + q - 1$. Each term of the (2X2) TPM will be the conditional probability $p_{ij} = P(I_t = j \mid I_{t-1} = i)$, or the probability of moving from state j to state i. Based on estimated transition probabilities different situation are possible (Ropert and Dundas, 2008), in the case of a 2-dimensional matrix :

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).

The balanced nature of our firm- level dataset avoids possible drawbacks of the TPM analysis. However, the discretisation of the continuous variable TFP might significantly affect the results. For this reasons, we have also defined a more restrictive approach to associate growth rates of TFP and innovation. In fact the simple adoption of positive growth rates might be misleading in presence of marginally negligible increases in the indicator. Furthermore, the simple use of positive growth rates might be sensitive to sectoral specificities. Hence, in the third matrix of Table 2 we identify a company as innovating in year t if its growth rate of TFP in the two previous years has fallen above the 25th percentile of distribution of all positive growth rates of the other companies in the same year and sector. In this case, we are implicitly focusing on the persistence of innovation among the sub sample of companies that are constantly able to significantly outperform their competitors in the same industry. In this case, the results seem to reflect the ones obtained by the studies which have used patent data: the observed persistence of innovation is higher when considering best performers. In order to assess the accuracy of these estimated transition probabilities we have applied a simple bootstrapping procedure with replacement to compute standard errors (Davison et al. 2006).

Table2 – Transition probability matrixes for different sub samples.

Complete sample (years1996-2005)		
	$INNO_t$	NOT $INNO_t$
$INNO_{t-1}$	67.59%	32.41%
NOT $INNO_{t-1}$	47.56%	52.44%

Sample with initial observation in year 2000		
	$INNO_t$	NOT $INNO_t$
$INNO_{t-1}$	65.70%	34.30%
NOT $INNO_{t-1}$	47.37%	52.63%

Innovation threshold at the 25th percentile		
	$INNO_t$	NOT $INNO_t$
$INNO_{t-1}$	69.54%	30.46%
NOT $INNO_{t-1}$	38.65%	61.35%

The data seem to provide initial evidence of significant persistence in innovation, as captured by positive growth rates of TFP. However, we claim that it is important to stress how the above results, although suggesting the presence of some form of inter-temporal stability in innovation effort, do not provide, yet, a sound answer to two key question: how much of the observed persistence can be labeled as true persistence driven only by previous innovation? To what extent the observed persistence is influenced by external factors? In the next section we introduce an econometric analysis specifically devoted to assessing these two points.

4.3.2. **PANEL DATA ANALYSIS**

In order to analyze the persistence of innovation along time we have constructed a time varying dummy variable ($INNO_t$) that equals one if a company has experienced a positive TFP growth rate over a two year period, between year t-2 and year t. We then apply different dynamic discrete choice models in which such variable is regressed against its past realization and a set of appropriate controls. In particular, we test the relationship between the innovation dummy and both internal and external factors. The former group includes a variable of firm size measured as the log of firms' total asset (SIZE), an indicator of the level of human capital as captured by the average wage (WAGE), the price-cost-margin as indicator of firms' profitability (PCM) and the financial leverage (LEV).

The second group of regressors accounts for changes along time in sectoral technological opportunities and for regional conditions. As previously highlighted, we claim that firms' capability to introduce technological innovations can be affected by the specific conditions of the local economic environment. For this reason, as controls for external conditions we include in the model specification a variable (REG) that for each company i equals the yearly average level of the TFP of all the other companies (included in our sample) and located in the same region of company i. This regressor is expected to capture general regional conditions potentially affecting productivity levels through time, such as the presence of knowledge intensive infrastructure, the local development of financial institutions or specific characteristics in the input markets.

Clearly, changes along time in firm-level TFP are likely to be affected also by non-geographically defined external factors. In order to account for sectoral dynamics of TFP we include in the model the variable SECT that for each company i equals the yearly average level of the TFP of all the other companies (included in our sample) belonging to the same 2-digit ATECO classification of company i. Since the innovation dummy variable is defined over a two year period, we have inserted the above mentioned controls with a lag.

As previously highlighted, 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 R&D costs previously incurred by a company, the cumulativity of 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 we expect to obtain a clearer view of the contribution of the different potential sources of the observed innovation persistence.

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

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

$$y_{it} = 1[y_{it}^{*} > 0]$$

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 .

Two different approaches can be adopted for handling such initial condition problem: Heckman (1981) suggests to specify 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. Here below we briefly illustrate and discuss the two methods. For sake of robustness in our analysis we have then applied both the methodologies adopting the model specifications proposed in some recent contributions.

The approach by Heckman (1981) suggests to specify a linearized approximation of the reduced form equation for the initial value (t=0) of the latent variable as follows:

$$y_{i0}^* = z_{i0}\pi + \eta_i \tag{2}$$

where z_{i0} is a vector of exogenous instruments and includes x_{i0}. The underlying assumption of such specification is that η_i is correlated with u_i (see eq. 1) but uncorrelated with ε_{it} for any t>0. Given a $\vartheta > 0$ we can then write the following relation:

$$\eta_i = \vartheta u_i + \varepsilon_{i0} \tag{3}$$

$$y_{i0}^* = z_{i0}\pi + \vartheta u_i + \varepsilon_{i0} \tag{4}$$

Given the specification of the initial observation (4), it is then possible to use the joint probability of the observed binary sequence (t=0,…t=T) with maximum likelihood for the estimation of the dynamic model. Stewart (2007) provides an application of this estimator[2]. In our case we have adopted as instruments in eq.2 firm level pre-sample variables (Size and PCM).

The approach suggested by Wooldridge (2005) tries to overcome the initial conditions problem by specifying the distribution of the individual error term as a function of all covariates and the initial realisation of the dependent variable. In particular, we follow the methodology applied by Peters (2008) which offers a simplification of the Wooldridge method, by

[2] The model has been estimated with the STATA routine redprob, developed by Stewart (2007). For more details see http://www2.warwick.ac.uk/fac/soc/economics/staff/faculty/stewart/stata

using time-averaged covariates as predictors of the individual effect, according to the following relationship:

$$u_i = \alpha_0 + \alpha_1 y_{i0} + \alpha_2 \bar{x}_i + c_i \tag{5}$$

$$\bar{x}_i = T^{-1} \sum_{t=1}^{T} x_{it} \tag{6}$$

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

$$u_i \mid y_{i0}, \bar{x}_i \approx N(\alpha_0 + \alpha_1 y_{i0} + \alpha_2 \bar{x}_i \ , \sigma_c^2] \tag{7}$$

$$P(y_{it} = 1 \mid y_{i0}, \ldots, y_{it-1}, x_i, \bar{x}_i, c_i) =$$

$$= \phi(\gamma y_{it-1} + \beta x_{it} + \alpha_0 + \alpha_1 y_{i0} + \alpha_2 \bar{x}_i \ + c_i) \tag{8}$$

This second methodology has the advantage of being less restrictive on exogeneity assumptions with respect to the Heckman's one. By a technical point of view the Wooldridge (2005) method amounts to estimating a dynamic random effect probit model in which regressors include a dummy representing the initial realisation of the dependent variable ($INNO_0$ in our case) and the time average of those covariates that are expected to be correlated to the individual effect (in our model AVGSIZE, AVGWAGE, AVGPCM). The model estimated with the Wooldridge approach provides the notable additional advantage of offering a direct estimate of the share of unobserved heterogeneity through the following relation:

$$\rho = \frac{\sigma_c^2}{1 + \sigma_c^2} \tag{9}$$

As recognized by Peters (2008) the dynamic random effect probit model might still suffer from endogeneity problems. To assess the impact of including variables that might fail the exogeneity assumption on the estimate for state dependent variable, we apply a stepwise procedure.

In Table 3 we report our results for different specifications of the persistence model estimated with the Wooldridge approach as implemented in Peters (2008). The results stress that, even after controlling for a number of internal and external factors, the probability of observing an innovation at time t is positively and significantly affected by the previous realization of the INNO variable.

Table 3 – Dynamic random effect probit model with the Wooldridge (2005) specification. Dependent variable $INNO_t$.

	Model I		Model II		Model III	
	coeff	std err	coeff	std err	coeff	std err
$INNO_{t-1}$	0.593	(0.013)	0.641	(0.013)	0.622	(0.137)
SIZE	0.041	(0.014)	0.048	(0.014)	0.048	(0.015)
WAGE			0.517	(0.042)	0.587	(0.042)
PCM			0.001	(0.002)	0.001	(0.002)
REG TFP			0.217	(0.064)	0.134	(0.065)
SECT TFP					3.391	(0.133)
$INNO_{t=0}$	0.067	(0.014)	0.067	(0.014)	0.064	(0.014)
AVGSIZE	-0.039	(0.015)	-0.042	(0.016)	-0.043	(0.016)
AVGWAGE			0.467	(0.056)	0.552	(0.056)
AVGPCM			-0.007	(0.009)	-0.007	(0.009)
Ind dummies	yes		yes		yes	
Time dummies	yes		yes		yes	
σ^2	0.459		0.448		0.434	
ρ	0.314		0.309		0.303	

It is worth clarifying that the result of the econometric estimates tests the role of a number of controlling factors upon the chances of observing a positive growth rate of TFP, rather than upon the probability that innovators keep introducing innovations along time. In this sense, we obtain that the fact of being located in a region characterized by higher levels of TFP of surrounding firms is positively associated to the probability of introducing some form of innovation. The value of the parameter ρ across the different specifications suggest that on average given our modeling structure unobservable heterogeneity still accounts for around 30% of the variance.

The stability of estimated coefficient across the different models in Table 3 suggests the absence of significant problems of endogeneity. The fact that in all models the initial condition is significant can be interpreted as signal of a positive relationship between firms' initial innovation status and the unobserved heterogeneity. The significance of the other variables is most important as it confirms the path dependent character of the non-ergodic persistence. Among the internal factors the levels of past human capital, as measured by average unit wage, significantly enhance the probability of subsequent innovation outcomes.

The effects of size have been estimated with two indicators: AVGSIZE and SIZE. The former is time-invariant. The latter is the yearly measure. Our results suggest that the AVGSIZE, i.e. the dimensional class to which each firms belongs has a negative effect. This result is perfectly aligned with the expectations based upon the Gibrat law. The results suggest, instead, that SIZE, i.e. the time varying dimension of the firm, has a positive effect. In the following Table 4 we report the results obtained for the model specification based on the Heckman (1981) approach. Also in this case we find a positive and significant correlation along time in the realizations of the innovation variable.

In both models (Table 3 and Table 4) the local context exerts a strong and positive role upon the persistence of innovation as measured by the levels of TFP of firms co-localized in the proximity within the same region. As expected, the access to the local pools of knowledge and the pecuniary knowledge externalities generated by the regional agglomeration of innovative firms favor the persistence of innovative activities. The intensity of innovation of the firms active in the same industries also favors the persistence of innovation. The stronger is the typical Schumpeterian rivalry among firms that rely upon the introduction of innovations as a competitive tool and the stronger is the persistence of innovation.

Table 4 - Dynamic random effect probit model with the the Heckman (1981) approach. Dependent variable: INNOt. Model estimated with the redprob the routine by Stewart (2007). Instruments for reduced form: pre-sample levels of SIZE, PCM and positive cash-flow dummy.

	Model II		Model III	
	coeff	std err	coeff	std err
$INNO_{t-1}$	0.625	(0.012)	0.605	(0.013)
SIZE	0.016	(0.004)	0.017	(0.004)
WAGE	0.276	(0.031)	0.301	(0.031)
PCM	-0.290	(0.023)	-0.293	(0.023)
REG TFP	0.250	(0.060)	0.187	(0.061)
SECT TFP			3.245	(0.132)
Ind dummies	Yes		yes	
Time dummies	Yes		yes	
Pseudo R^2	0.121		0.131	

Our results confirm the non-ergodic persistence of total factor productivity growth and suggest that such persistence is affected by contingent factors that are both internal and external to each firm. The results can be interpreted as a test of the claim that the persistence is path rather than past dependent. Contingent factors, such as human capital, market rivalry and geographic location would not be significant when the persistence is past dependent because the original conditions would play an exhaustive causal role.

5. CONCLUSIONS

This paper provides empirical evidence upon the path dependent persistence of innovation activities, as measured by total factor productivity levels (TFP). The empirical analysis of firm level TFP for a sample of 7020 Italian manufacturing companies observed during years 1996-2005 confirms that firms that have been able to improve the general efficiency of their production process at time t are likely to keep innovating in the following periods of time, more than firms that never innovated before. Such a persistence is path dependent, as opposed to past dependent, as it is shaped by a number of complementary and contingent factors that shape locally the dynamics of the process by means of both reductions and increases in the matrix of transition probability.

The evidence in fact confirms that the dynamics of the process is non-ergodic but is not past-dependent as it is not determined exclusively by the original conditions. The econometric results confirm that it is affected by contingent and localized events so as to acquire the typical features of a path dependent process where the past dependent effects of the early conditions are re-shaped and influenced by the sequence of events that contribute, at each point in time, the actual sequence of events.

At each point in time the probability of introduction of further innovations is indeed affected by the sequence of innovations introduced in the past but it is also conditional to the actual levels of internal dynamic capabilities of each firm to accumulate and exploit of technological knowledge and human capital, the amount of external knowledge that is available in the regional proximities, and the competitive pressure of innovative rivals active in the same product markets.

6. REFERENCES

Alfranca, O., Rama, R., von Tunzelmann, N. (2002), A patent analysis of global food and beverage firms: The persistence of innovation, *Agribusiness* 18, 349 – 368.

Antonelli, C. (1997), The economics of path-dependence in industrial organization, *International Journal of Industrial Organization* 15, 643-675.

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

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

Arrow, K.J. (1974), *The limits of organization*, W.W.Norton, New York.

Blundell R., Bond, S. (1998), Initial conditions and moment restrictions in dynamic panel data models, *Journal of Econometrics* 87, 115-143.

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

Cefis, E., Orsenigo, L. (2001), The persistence of innovative activities. A cross-countries and cross-sectors comparative analysis, *Research Policy* 30, 1139-1158.

Cefis, E., Ciccarelli, M. (2005), Profit differentials and innovation, *Economics of Innovation and New Technology* 14, 43-61.

David, P. A. (1985), Clio and the economics of QWERTY, *American Economic Review* 75, 332-37.

David, P.A. (1994), Positive feedbacks and research productivity in science: Reopening another black box, in Granstrand, O. (ed.), *The economics of technology*, Elsevier North Holland, Amsterdam.

David, P.A. (1997), Path dependence and the quest for historical economics: One more chorus of ballad of QWERTY, *Oxford University Economic and Social History Series 020, Economics Group*, Nuffield College, University of Oxford.

David, P. A. (2007), Path dependence: A foundational concept for historical social science, *Cliometrica: Journal of Historical Economics and Econometric History* 1, 91-114

Davison, A. C.; Hinkley, D. (2006), *Bootstrap methods and their applications*, 8th, Cambridge Series in Statistical and Probabilistic Mathematics.

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.

Foster, L., Haltiwanger, J. and C.J. Krizan (2002), The link between aggregate and micro productivity growth: Evidence from retail trade, *NBER Working Paper*.

Geroski, P.(1994), *Market structure corporate performance and innovative activity*, Oxford University Press, Oxford.

Gruber, H. (1992), Persistence of leadership in product innovation, *Journal of Industrial Economics* 40, 359-375.

Heckman, J.J. (1981), The incidental parameters problem and the problem of initial conditions in estimating a discrete time - discrete data stochastic process, in C.F. Manski and D. McFadden (eds.). *Structural analysis of discrete data with econometric applications*, MIT Press, Cambridge.

Jacobs, J. (1969), The economy of cities, Random House, New York.

Latham, W.R., Le Bas, C. (eds.) (2006), *The economics of persistent innovation: An evolutionary view*, Springer, Berlin.

Malerba, F., Orsenigo, L., Petretto, P. (1997), Persistence of innovative activities sectoral patters of innovation and international technological specialization, *International Journal of Industrial Organization* 15, 801-826.

Olley S., Pakes, A. (1996), The dynamics of productivity in the telecommunications equipment industry, *Econometrica* 64, 1263–1297.

Parisi, M.L., Schiantarelli, F., Sembenelli, A. (2006) Productivity innovation and R&D: Microevidence for Italy, *European Economic Review* 50, 2037-2061.

Penrose, E., (1959), *The theory of the growth of the firm*, Oxford University Press, Oxford.

Peters, B. (2008), Persistence of innovation: Stylized facts and panel data evidence, *Journal of Technology Transfer*, forthcoming.

Raymond, W., Mohnen, P., Palm, F.C., Schim Van Der Loeff, S. (2006), Persistence of innovation in Dutch manufacturing: Is it spurious? CESifo Working Paper Series No. 1681

Roodman, D. (2006), An introduction to “difference” and “system” GMM in Stata, Working Paper n. 103, Center for Global Development. www.cgdev.org

Roper, S., Hewitt-Dundas, N. (2008), Innovation persistence: Survey and case-study evidence, *Research Policy* 37, 149-162.

Scherer, F.M., Harhoff, D. (2000), Technology policy for a world of skew-distribution outcomes, *Research Policy* 29, 559–566.

Stewart, M.B. (2007), “The inter-related dynamics of unemployment and low-wage employment”, *Journal of Applied Econometrics*, 22, 511 - 531

Stiglitz, J.E. (1987), Learning to learn localized learning and technological progress, in Dasgupta, P. and Stoneman, P. (eds.), *Economic policy and technological performance*, Cambridge University Press, Cambridge.

Teece, D., Pisano, G. (1994), The dynamic capabilities of firms: An introduction, *Industrial and Corporate Change* 3, 537-555.

Wooldridge, J. (2005), Simple solutions to the initial conditions. Problem in dynamic nonlinear panel data models with unobserved heterogeneity, *Journal of Applied Econometrics* 20, 39–54.

ANNEX 1

Table 5- Sectoral distribution of companies included in the sample

Industry – ATECO Classification	**Number of companies**	**Percentage**
Food and beverages	561	8.0%
Textile	607	8.6%
Textile product industry	212	3.0%
Leather and leather products manufacturing	249	3.5%
Wood and wood products manufacturing	155	2.2%
Pulp, paper and paper products manufacturing	174	2.5%
Printing	193	2.7%
Chemical industry	401	5.7%
Plastics and rubber manufacturing	421	6.0%
Non-metallic mineral product manufacturing	390	5.6%
Metallurgy	275	3.9%
Metal products manufacturing	983	14.0%
Mechanical machinery and equipment manufacturing	1,078	15.4%
Computer and electronic manufacturing	24	0.3%
Electrical machinery and equipment manufacturing	287	4.1%
Telecommunication machinery and equipment	91	1.3%
Medical, optical and precision equipment	143	2.0%
Transportation equipment manufacturing	122	1.7%
Other transport equipment manufacturing	61	0.9%
Furniture	487	6.9%
Software	106	1.5%
Total	7,020	100.0%