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Path Dependent Patterns of Persistence in Productivity Growth

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ABSTRACT. This paper contributes to the analysis of the persistence of firm productivity, here measured by the total factor productivity (TFP), and highlights its path dependent characteristics. The study contributes to the literature on persistence in productivity along four main lines. First, it develops a conceptual framework that links the persistence in productivity performance to persistence at the firm level in innovative activities, which include the adoption and imitation of innovations introduced by third parties. Second, it shows how the internal characteristics of companies, including the propensity of managers to leverage dynamic capabilities, can shape the dynamics of the process. Third, it confirms that external factors, such as the access to local pools of knowledge and the dynamics of economic activity, have relevant effects on persistence and shape its evolution along its path. Fourth, the use of Multiple Transition Probability Matrices (MTPMs) and the subsequent econometric analysis provides substantial evidence on the relevance of the crucial distinction, within non-ergodic dynamics, between past dependent processes, characterized by full hysteretic irreversibility, and path dependent processes in which events that take place along the process may affect its direction and pace.

KEY-WORDS: PRODUCTIVITY; PERSISTENCE; PAST DEPENDENCE; PATH DEPENDENCE; TFP
JEL CODES: O31, C23, C25, L20, M20

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1. Introduction

Over the past few decades a broad range of research activities have been dedicated to the study of productivity growth sources. While traditionally the empirical analyses were based on macro or industry-level aggregate data, a large number of studies, based on micro data, has recently been produced, due to the increasing availability of firm level data (for extensive reviews see Bartelsman and Doms, 2000; Ahn, 2000; Foster et al., 2001; Syverson, 2010).

The discovery of ubiquitous, extensive, and persistent productivity differences has shaped research agendas in a number of fields. Macroeconomists decompose aggregate productivity growth into various micro-components, with the aim of providing a better understanding of the sources of such growth. Models of economic fluctuations driven by productivity shocks, are increasingly being enriched to account for micro-level patterns, and are estimated and tested using plant or firm level productivity data rather than aggregates, since micro productivity data offer a level of resolution that is unattainable with aggregated data (Bartelsman et al., 2009).

Two main lessons have been learned from this extensive field of research. First, the quantity of productivity dispersion is extremely large i.e. some firms are remarkably more efficient than others. Second, firms that are highly productive today are more than likely to be highly productive tomorrow. In other words, the literature has clearly pointed out the existence of a high degree of persistence in productivity differences across producers (Bartelsman and Doms, 2000; Syverson, 2010).

The identification of such high productivity dispersion and persistence across producers, has led to the emergence of a huge amount of empirical literature that attempts to explain the sources of these productivity patterns. This evidence casts major doubts and raises substantial criticisms about the new growth theory, according to which the rates of productivity growth and of the introduction of technological innovations should be homogeneous across firms that belong to the same system (Aghion and Howitt, 1997; Antonelli, 1997). The relevance of this empirical evidence and its theoretical implications have led to the identification of a number of factors that could determine systematic differences in the productivity performances of producers. In this context, the capability of firms to generate and exploit technological knowledge plays a central role.

A great deal of effort has been devoted to quantifying the contribution of technological change to productivity growth. The seminal contributions by Mansfield (1965) and Griliches (1979) explicitly considered measures of technological change (usually R&D expenditure) in models on the determinants of productivity growth, and found important evidence in favour of the hypothesis of a positive effect of R&D on productivity dynamics. The impact of innovation on productivity has been further explored in studies that use innovation-survey data. These studies have confirmed the importance of innovation in sustaining productivity, together with the role played by structural factors, and have shown strong cross-sector and cross-country differences (Crépon, Duguet and Mairesse, 1998; Hall and Mairesse, 2006; Crespi and Pianta, 2008; OECD, 2009).

Recently, a great deal of research has been conducted to evaluate the impact of the emergence and the differentiated rates of the adoption of a new technological paradigm based on ICTs on productivity growth. At both the macro level (Jorgenson and Stiroh, 2000; Jorgenson et al., 2008; van Ark et al., 2008) and at the micro level (Brynjolfsson and Hitt, 2000; and more recently Bartelsman et al., 2009; Faggio et al., 2009) the role of ICTs has been found to be crucial to support productivity growth.

Less attention has been paid to the role of the adoption of innovations in increasing productivity levels. However, productivity can increase not only because of the original introduction of a new product or a new process, but also, and to a great extent, because of the timely adoption of new product innovations in upstream industries that specialize in capital and intermediary goods and due to the imitation of product innovations previously introduced by other firms on the same markets. Adoption and imitation can no longer be regarded as the result of passive and automatic conduct. Competence and knowledge are necessary to chose the best possible innovation from the many that are introduced at each point in time and to adapt it to the specific and highly idiosyncratic characteristics of the production processes and the product and factor markets in which each firm operates.

The literature has also identified other firm specific characteristics that are capable of affecting the productivity performance of producers. Particular attention has been devoted to assessing the impact of human capital and the quality of management practices on different measures of productivity and firm performance (for recent contributions see McEvily and Chakravarthy, 2002; Ilmakunnas et al., 2004; Galindo-Rueda, 2005; Bou and Satorra, 2007; Bloom and Van Reenen, 2007 and 2010). Parallel

studies have investigated, with mixed results, the role of size and financial structure (Geroski, 1994; Sutton, 1997; Bottazzi et al., 2008), but also the role of external productivity performance drivers, such as knowledge spillovers related to agglomeration effects or the geographic location of the activities of firms (Griffith et al., 2007).
Remarkably, only rarely have the connections between the literature on the persistence of innovation and the persistence in productivity been explicitly discussed. The work by Geroski and collegues represents an important exception in this respect (Geroski et al., 2003 and 2009). These studies have shown that the superior productivity growth of firms does not persist very long. However, in the first paper it was stated that firms innovate - or more precisely patent- very irregularly, and this leads to random growth rates in productivity, but, in the second study, the authors found evidence that innovative firms were likely to display persistently higher productivity growth performance than non-innovative firms. This evidence opens up new research directions concerning the investigation of the links between persistence in innovation and in productivity performance.

In this paper, we argue that the hysteretic nature of productivity performance is closely linked to the persistence observed in innovation activities, which not only include the introduction of innovation, but also the adoption and imitation of innovations introduced by third parties. In this respect, advantage has been taken of the recent developments in the economics of innovation that have paid attention to the analysis of innovation persistence, and have found evidence of persistence in innovative activities, which, however, depends on the indicators that have been employed (Malerba et al., 1997; Cefis, 2003; Peters, 2008; Roper and Dundas, 2008; Antonelli et al., 2012, 2013).
Our interpretation of the results obtained from this literature is that this coupled persistence reflects the non-random nature of innovation activities. We argue in particular that this evidence suggests that the persistence of innovation exhibits the typical dynamic traits of a non-ergodic process in which history is important. In this context, it seems more relevant to investigate the specific dynamic properties of innovation persistence.

A non-ergodic process may in fact be either past dependent, when the features of the process are fully and exhaustively defined at its onset, or path dependent when irreversibility affects its dynamics and yet small, contingent events along the process may change its key characteristics, such as path, speed and destination (David, 1997; Antonelli, 1997). The introduction – imitation and adoption- 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, exerts path dependent, rather than past dependent, effects (Antonelli, 2008). In order to study the nature and effects of this process, a general measure of production efficiency is considered, that is total factor productivity, as it has been assumed that it can capture a broad understanding of the role of innovation, including the effects of the adoption of new processes, new intermediary inputs introduced by suppliers in upstream factor markets and the imitation of new products introduced in the same and adjacent product markets. In this respect, the aim of this work is twofold. First, it is an attempt to contribute to the literature on the persistence of productivity through an analysis on the dynamics of TFP in a large sample of Italian firms. Second, the characteristics of the persistence in productivity are qualified and its determinants are explored. In so doing, the literature on the persistence of productivity is related to the literature on the persistence of innovation and path dependence.

In this paper we build on these concepts and test to what extent the dynamics of productivity growth is affected by the characteristics of firms (including strategic managerial decisions on R&D efforts, vertical integration and financial structure) and by external factors (including the local availability of knowledge and the dynamics of the business cycle). In this perspective, an attempt has been made to assess the role of different sources of productivity persistence: internal dynamic capabilities and access to external knowledge. In this way we try to qualify the form of dynamics at work through the identification of its path dependent characteristics.

The remaining part of the paper is structured as follows. The literature on the persistence in productivity and innovation activities is reviewed in Section 2. The hypotheses and the research design of this study are outlined in Section 3. The econometric evidence is presented in Section 4. The main results are summarized in the conclusions.

2. The persistence of productivity and innovation

2.1 The persistence of productivity

Under the assumption of random productivity differences across producers, relative productivity would be uncorrelated from one period to another. There would be no persistence in the productivity distribution, and the TFP of a producer in one period would have no predictive power on the TFP of another period. However, empirical investigations have shown that there are large and persistent differences in productivity across plants and firms in the same industry (Bartelsman and Doms 2000). When analyzing persistence in productivity, many studies have followed an approach based on transition probability matrices relative to the plant/firm productivity distribution (see, for example, Baily et al., 1992 and Bartelsman and Dhrymes, 1998). The calculated transition matrices exhibit large diagonal and near-diagonal elements, indicating that producers that are high in the distribution in one period tend to continue to have an high rank in the distribution in the subsequent periods.

Baily et al. (1992) ranked the plants in their sample regarding the 1972-1988 period according to their relative productivity for each year and divided them into quintiles. They then calculated a transition matrix, which highlighted "an enormous amount of persistence in the productivity distribution". Of all the plants that were in the first quintile in 1972, a weighted 60.75 percent was again in the first quintile in 1977. Of all the plants that were in the first quintile in 1977, a weighted 52.89 percent of them had come from the first quintile in 1972. The persistence in the 10-year transitions was even stronger than that found for 5 years. More than 58 percent of the plants in the top quintile in 1972, were still in the top two quintiles in 1982. Bartelsman and Dhrymes (1998) found a similar high degree of persistence in productivity ranking through an examination of the behaviour of TFPs in selected industries, over the 1972–1986 period in the USA. They showed, in particular, that about 60 percent of the plant-year observations did not move away by more than one decile from their previous rank. Moreover, they found that larger plants exhibited more stability, and that the probability of staying close (one decile) to the previous position increased with age and size. They concluded that this evidence could have been the result of some form of "learning by doing" that may characterize the evolution of the productivity performance of plants.

More recently Giannangeli and Gomez-Salvador (2008) have used annual account data over the 1993-2003 period for a balanced panel of manufacturing firms for a selected panel of five European countries. They have found a high degree of persistence of the relative efficiency of firms. Around 25% of firms in all countries considered in the analysis remained in the middle of the distribution, while more than half of the sample persistently remained at the top and bottom parts of the distribution. The authors have concluded that the high persistence of relative productivity levels suggests that firm efficiency levels are structurally different from firm to firm.

As far as Italy is concerned, Bottazzi et al. (2009) have carried out an analysis based on a large panel of Italian firms active in both Manufacturing and Services, during the 1998-2003 period, which has confirmed the presence of a strong and positive correlation in productivity over time. Bottazzi and colleagues, building on the seminal work by Muller (1976), tried to explore the links between the persistence in productivity and profitability, and have found that more efficient firms also tend to be more profitable.

Although these empirical investigations have shown that there are large and persistent differences in productivity levels across plants and firms, productivity growth rates have usually been found to exhibit an important transitory component. Baily et al. (1992) and Dwyer (1998) presented clear evidence of regression to the mean effects in productivity growth regressions. Similarly, Bartelsman and Dhrymes (1998) detected a strong negative correlation between a plant's growth rate over a five-year period and its productivity growth over the prior five years. Giannangeli and Gomez-Salvador (2008) instead showed that when lagged productivity growth is included in the econometric model, it results to be positive and significant, thus indicating some persistence in labour productivity growth at the firm level.

As previously mentioned in the introduction, Gerosky et al. (2003 and 2009) specifically investigated persistence in productivity growth. In the first paper, using a sample of 147 UK firms observed continuously for more than 30 years, they showed that growth rates are highly variable over time and that the differences in growth rates between firms do not persist for very long. This outcome was considered to be due to the random nature of the innovative activities of firms, which translates into random shocks on productivity. Again, in the second paper, they found that, in general, individual firms do not outperform their peers for very long, when stable firm characteristics, via firm fixed effects, are accounted for. However, the analysis showed that the few instances of sustained productivity growth performance that had been observed appeared to have been triggered mainly by prior innovative activity and the disciplining effect of corporate debt. The effects of the introduction of innovations on market power and the competitive advantage, especially on product markets, help to explain the persistence of productivity growth. Bronnenberg, Sanjay, Dhar, Dubé (2009), have offered evidence of a persistent "early entry" advantage for brands in 34 consumer packaged goods industries across the 50 largest U.S. cities. The current market shares are higher in markets closer to a brand's historic city of origin than in those that are farther. Their study on the order of entry among the top brands in each of the markets makes it possible to identify an early entry effect on a brand's current market share and perceived quality across U.S. cities. The magnitude of this effect usuallty drives the rank order of market shares and perceived quality levels across cities.

The relevance of the role of innovation in determining the persistence of productivity performances can be better understood by impinging on the recent literature on the persistence of innovation.

2.2 The persistence of innovative activities

The empirical analysis on the persistence of innovation activities is rather a recent undertaking in 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) paved the way to this new area of investigation. 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 over time.

The evidence from the literature is mixed. Most studies identify weak elements of persistency but do not provide convincing consensus about its determinants or, more importantly, about the specific kind of dynamic process. In particular, the works that have used patents as a reliable indicator of innovation suggest that persistence is weak and only exhibits strong values in the case of heavy patentees.

While the econometric evidence provided by Malerba et al. (1997) showed that innovative activity is persistent and plays an important role in explaining the concentration of technological activity as well as the stability of the ranking of innovators and their innovative intensity, Geroski, Van Reenen and Walters (1997) found that only a few firms are persistently innovative. Cefis and Orsenigo (2001) and Cefis (2003) have applied a transition probability matrix to analyze the persistence of innovative activities on different samples of EU firms and confirmed the weak persistence of patenting activity. The analysis of the transition probability matrixes has shown little persistence in general, characterized by a strong threshold effect. In other words, only great innovators have a stronger probability to keep innovating. Alfranca, Rama and von Tunzelmann (2002), who studied the persistence of innovation in a specific sector with a focus on a well-identified group of firms observed from 1977 to 1994, and presented a detailed case-study evidence that was able to carefully identify specific innovations, found stronger indication of innovation persistence on the basis of patent data. Their results showed that the 17 year patent series was not consistent with a random walk model. The evidence confirmed that the observed firms exhibited a stable pattern of technological accumulation in which "success breeds success". Finally, Latham and Le Bas (2006) have provided a systematic investigation of the persistence of innovation based on an analysis of French and US patents. Their results have confirmed the persistence of innovation, but only, and mainly, over a limited time span. Latham and Le Bas also tested the hypothesis that size and profitability exert a greater positive effect on the spell of innovation activities: the larger the firms and the larger their profitability, the longer the time spell over which the firms are able to sustain a sequence of innovations.

Empirical analyses based on survey data have found stronger evidence of persistence in innovation activities than the works that used patents as an innovation indicator. However, such studies have also highlighted that the choice of the indicator to measure the extent to which the introduction of innovation has a hysteretic nature is not trivial and that the results seem to be sensitive to the indicator that is chosen (Duguet and Monjon, 2004).

Among these analyses, Peters (2008) has provided relevant evidence in favour of persistence of the innovation activities of firms, both in terms of innovations inputs, such as R&D activities, and innovation outputs as measured by the number of innovations introduced by German manufacturing and service firms in the years 1994-2002. The research relied on the Manheim Innovation Panel of the ZEW and was based on the Community Innovation Survey (CIS). The persistence of innovative activities has been found to be determined by the levels of skills, the support of public funding, financial liquidity and size. A parallel analysis on Norwegian CIS conducted by Clausen et al. (2012) has found that R&D-intensive and science-based companies are more likely to be persistent innovators.

Such evidence has been confirmed –at the plant level- by Roper and Hewitt-Dundas (2008), who have used innovation survey data and show that, in the case of 3604 plants covered by the Irish Innovative Panel in the 1991-2002 period, both product and process innovations are strongly persistent. Finally, Antonelli et al. (2012, 2013) have contributed to the analysis of the persistence of innovation activities, measured by different innovation indicators. Their results confirm the presence of significant persistence in innovation. However, the levels of persistence captured by the inter-temporal elasticity between the innovation indicators have been found to be significantly different according to the typology of innovation considered. The highest level of persistence was found for R&D investments and product innovation, which showed the actual presence of significant entry and exit barriers to innovative activities. The present paper, with respect to these previous analyses, focuses specifically on measuring persistence in productivity growth and on investigating its sources through the introduction of the role of internal capabilities and management strategies of firms into the analysis, as well as the influence of the (external) local and macroeconomic contexts.

3. THE CHARACTERISTICS AND THE SOURCES OF PERSISTENCE

The reviewed evidence suggests that innovation persistence is relevant and substantial. However, it is also characterized by high levels of dispersion and volatility. It seems clear that the introduction, adoption and imitation of one innovation is not sufficient to warrant the ability to keep innovating and enjoying increases in total factor productivity. Innovation persistence occurs when a number of complementary and contingent factors sustain and strengthen the hysteresis generated by the first innovation. The introduction, adoption and imitation of a single innovation in fact has potentially long term effects that only display all their benefits when a number of accompanying factors contribute to make the actual dynamics of persistence operational. The identification of these patterns of persistence, in both innovation and productivity raises, a number of questions on the characteristics and the sources of such processes.

In what follows, it is argued that persistence in production efficiency reflects the path dependent nature of innovation activities. In order to better understand the nature of this process we chose to employ an indicator able to capture the general efficiency of firms, that is total factor productivity. It has in fact been assumed that total factor productivity is capable of reflecting the levels of a broad range of innovation capabilities, and their direct and indirect consequences on the performances of firms. Total factor productivity measures account for the economic effects of both the adoption of innovations, and their introduction. The timely adoption of innovations is the result of intentional decision making, which involves important effects on the performance of firms, including the general level of efficiency. Hence, the study of the persistence of total factor productivity growth of firms, offers an interesting perspective for the analysis of the economic consequences of persistency in innovation capabilities.

In the authors' opinion, innovation capability consists of both the command of technological, organizational and commercial knowledge and in the ability to exploit it through the appropriation of the results of the introduction of technological innovations. Both the introduction and the adoption of an innovation are in fact related to the systematic capability to generate new knowledge, to apply it to the broad array of activities that firms carry out and to exploit it, while retaining a consistent share of the benefits engendered by the introduction of innovations. So far, our notion of innovation capability is quite broad 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 on which firms operate, including the adoption of innovations generated elsewhere. Moreover, it stresses the role of the capability to exploit new technological knowledge in order to obtain an increase in performance levels.

Since cumulative forces, substantial irreversibility and positive feedbacks shape innovative activities, the related generation of new knowledge and its economic exploitation, it is here claimed that total factor productivity growth is a persistent process when a number of complementary and contingent factors sustain its duration and shape its dynamics. Such a claim is mainly built on the following arguments:

A) The generation of technological knowledge is an activity that is characterized by significant indivisibility and learning. Knowledge indivisibility and learning to learn exerts strong cumulative effects (Stiglitz, 1987) that the burden of knowledge can only mitigate to a limited extent (Jones, 2009).

B) The generation of new knowledge and the introduction, adoption and imitation of innovations are the result of the creation, within corporations, of new functional routines and of research and development laboratories as well as of the structure of the communication networks that qualify access to external knowledge. These 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 (Schumpeter, 1942; Chandler, 1977 and 1990; 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 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 that are 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) Some innovative firms are able to command market power and enjoy substantial barriers to entry that favour the exploitation of innovations. This, in turn, increases knowledge appropriability levels and hence both incentives and financial resources to persist in the introduction of innovations. Such innovative firms are in fact more able to implement internal markets in which innovative undertakings can match financial liquidity made available by previous innovations.

E) The repeated interaction between the accumulation of knowledge, and the creation of routines to valorize and exploit it eventually leads to the creation of dynamic capabilities that favour the systematic reliance on innovation as a competitive tool (Teece and Pisano, 1994; Teece, 2007).

F) The timely and effective adoption and imitation of innovations introduced by third parties, but which are able to fit the idiosyncratic characteristics of the production processes and the product and factor markets on which each firm operates, requires competence and knowledge. Firms are continuously exposed to a large variety of tentative innovations that are introduced on the same product markets by both competitors and by suppliers on upstream factor markets. The adoption and imitation of the ‘right’ innovations is the result of knowledge intensive activities and requires a great

deal of effort, in terms of their adaptation to the specific characteristics of the firm. The more and the faster a firm is able to adopt and imitate the 'right' innovations, the greater the accumulation of internal competence and expertise. At the same time, it seems clear that the larger the internal stock of competence, the greater the chances of taking advantage of innovations being introduced by third parties on both the product and factor markets. A virtuous, self-feeding process is likely on the one hand to shape the relationship between adoption and imitation and, on the other between competence and knowledge.
In this context, a firm is shaped but not necessarily trapped by its past. Management strategies appear to be crucial to sustain superior productivity performance over time through investment choices and other decisions related to the leveraging of dynamic capabilities and the exploitation of strategic assets. Managerial contingencies in fact affect the non-ergodic dynamics of TFP growth persistence.

In addition to this set of hypotheses concerning internal factors, we highlight the role of external elements, such as knowledge externalities and market forces. As the economics of knowledge suggests, different forms of external knowledge, i.e. scientific, commercial, technological and organizational, as well as different kinds of activities close to R&D activities and learning, such as searching, networking, absorption and scientific outsourcing, are required to generate and exploit new technological knowledge. The macroeconomic context and the type of rivalry at work within product markets contribute to qualify the context in which innovation persistence takes place. Thus, the external conditions, together with the internal conditions, that is the actual levels of dynamic capabilities, are important because:

G) the quality of the local knowledge pools provides access to external knowledge, which is an essential complementary input for the generation of technological knowledge. The role of this factor is so relevant that it exerts a specific and localized effect on the persistence of the innovative process.

H) the strength of the Schumpeterian rivalry plays a crucial role as it qualifies the intensity, frequency and variety of introductions of innovations on factor and product markets, with consequent positive effects on the likelihood of firms being able to adopt and imitate timely and effectively innovations that would make it possible for them to increase their total factor productivity. The stronger the Schumpeterian rivalry, the stronger the persistence of the increase in productivity levels that stems from the timely and effective adoption and imitation of innovations introduced by third parties.

In short, since innovation and hence TFP growth persistence are affected by external and internal factors that exhibit relevant contingencies we argue that the non-ergodic process at work exhibits the intrinsic characteristics of path rather than past dependence. Innovation persistence would be past dependent, and hence fully determined by the introduction of the first innovation, if firms built long-lasting innovating capabilities after the introduction of the first innovation. More generally, innovation and TFP growth persistence would display the intrinsic features of past dependence if, and when, its duration could be defined *ex-ante* as if it were determined exclusively by the initial characteristics of the firm. It is here instead contended that persistence is affected by contingent factors, such as knowledge externalities, the evolving market conditions and managerial styles. The access conditions to the local pools of knowledge that engender externalities at the firm level are clearly endogenous to the system as they are emergent properties of a system that is itself exposed to changes at both macro and the meso levels. For the same reason, it is argued that the internal characteristics that affect innovation persistence are subject to a time variability which shapes the dynamics of the process in a step-wise manner. Hence, persistence is path dependent rather than past dependent: irreversibility shapes the process together with a number of contingent and localized conditions that exert significant effects on the non-ergodic dynamics of the process and change its path, its speed and its duration (David, 1997 and 2007; Antonelli, 2008).

In order to test the relevance of these arguments, a two-step empirical strategy has been set up. In a first step the analysis has been focused on the identification of persistence in total factor productivity growth through Multiple Transition Probability Matrices (MTPM). MTPM differ from standard Transition Probability Matrices (TPM). TPMs are in fact computed over the full period of time under consideration. The assumption is that TPMs are able to take into account contingent changes that may take place within that period of time. MTPMs, instead, are computed using variations in different sub-periods. The implementation of MTPMs is appropriate when the changes that take along the process are expected to have significant effects. MTPMs are expected to function successfully, when they make it possible to identify non-ergodic processes that are influenced by events that take place during the process. As such, the implementation of MTPMs is consistent with the hypothesis that the persistence of innovative activities is a path-dependent process. In other words, significant results of MTPMs confirm whether a process is path dependent or past dependent. For the latter, the variations along the period are not in fact statistically significant. In the second step, the analysis has been concentrated on the determinants of the path dependent persistence in order to qualify the role of the contingent events that affect the dynamics at work, including non-observable heterogeneity.

4. THE EMPIRICAL ANALYSES

4.1 Dataset

The dataset is based on financial accounting data from a large sample of Italian manufacturing companies, observed over the years 1996-2005. The original data were extracted from the AIDA database provided by Bureaux Van Dick, which reports complete financial accounting data for public and private Italian firms with a turnover greater than 0.5 million Euros. The companies included in the analysis were founded before 1995, were registered in a manufacturing sector according to the Italian ATECO classification, and were still active by the end of 2005. All the companies with at least 15 employees at the end of the 1995 fiscal year have been included. After collecting balance sheet data, all the companies with missing values were dropped. In order to drop outliers, due to possible errors in the data source, we computed a number of financial ratios and yearly growth rates of employees, sales and fixed capital stock. After a manual checking we eventually dropped 45 companies. We ended up with a balanced panel of 7020 companies. All financial data have been deflated according to a sectoral three-digit deflator using year 2000 basic prices. In the following table we show the sectoral distribution of the companies.

The firm level TFP has been calculated using Cobb-Douglas production functions with constant return to scale for each industry included in the sample .

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

where:

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

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

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

In order to compute the capital stock through time a perpetual inventory technique was applied according to which the first year accounting data i.e. year 1996, in the present case, are used as the 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.[2] The investment parameter ($I_{i,t,}$) has been computed as the yearly variation in the net fixed capital in the companies' balance sheets plus yearly amortizations. Hence, the time series of fixed capital is defined as:

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

In order to identify the parameter β at industry level to compute equation 2, the following equation has been estimated for each industry:

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

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. Additional variables used in the econometric analysis include size, return on equity, leverage, an indicator of vertical integration, an indicator of debt maturity composition and intangible intensity,

[2] The level of yearly depreciation of the physical capital was chosen following the approach applied in previous studies that applied perpetual inventory techniques to estimate yearly fixed capital levels, adopting depreciation parameters in the 5%-10% range for physical capital. Since the adopted depreciation parameter is constant across industries changes should not be expected in the significance of estimate coefficients for slight changes in δ.

computed as the yearly incidence of intangible to tangible assets[3]. The description and the summary statistics for these variables are reported in Table 2.

In order to analyse the dynamics of firm level TFP growth rates we have calculated the variable ΔTFP, defined as the logarithmic growth rate of the TFP level between year t-3 and year t:

$$\Delta TFP_{i,t} = \log(TFP_{i,t}) - \log(TFP_{i,t-3}) \tag{4}$$

We then proceeded to a classification of the values taken from the variable $\Delta TFP_{i,t}$ on the basis of the distribution of the TFP growth rates of all the companies in the same sector of company i between year t-3 and year t. This procedure allows us to evaluate the persistence of firm level TFP growth rates, taking into account industry specific trends. In particular, we will analyse the probability of a company's TFP growth rate is being persistently located within a specific quantile of the distribution of TFP growth rates of all companies in the same industry[4]. Sensitivity analyses have been conducted to assess whether, and to what extent, the thresholds adopted for the discretisation of the TFP growth rate distribution (e. g. using tertiles or quartiles) affect the estimated intensity of persistence.

Two complementary approaches have been followed in the empirical analysis. Initially, we investigate the presence of firm-level persistence by means of transition probability matrices (TPM). Then, we explore firm-level persistence by means of discrete choice

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[3] R&D expenditures is the traditional indicator used to measure the amount of internal efforts made to generate new technological knowledge. R&D statistics in fact only measure a partial amount of the overall effort that firms make to introduce new technologies. Internal learning activities are not accounted for, and neither is the cost to access external knowledge. Moreover, the actual efficiency of the research activities is not considered as R&D activities only partially measure some inputs in the process. Additional issues that are specific of the Italian institutional and empirical evidence need to be considered. The Italian manufacturing industry is characterized by a geographical clustering of many small firms in specialized industrial districts. There are only a few large firms. Reliable statistical evidence on R&D expenditures is missing. Official R&D statistics are based upon data collected from only 2200 agents (firms or research organizations). As a consequence, official R&D statistics provide a picture of the research activities conducted by a small portion of the economic activity carried out in the country. Small firms rarely reply to the detailed and time-consuming questionnaires that are used as an indispensable tool for the collection of R&D data which are not requested for the compilation of annual reports. However, accountancy rules coupled with fiscal allowances, provide excellent and reliable evidence on the stocks of intangible capital, which include capitalised research expenditures as well as purchasing costs for patents and licences and the costs incurred to build and implement brands and know how. It seemed appropriate to rely upon the figures that are publicly available in all the annual reports to obtain a reliable measure of the efforts undertaken to generate new technological knowledge.

[4] This measure of persistence is substantially different from that adopted in Antonelli et al. (2013) as in the previous study the state variable simply reflected the existence of positive changes in TFP over time.

panel data models, based on the estimator proposed by Wooldridge (2005). While the initial TPM approach was expected to provide only summary evidence on the persistence of the TFP growth rates of firms over time, the panel data analysis was aimed at identifying true state persistence after controlling for relevant contingent factors. Table 1 reports summary statistics of the main variables in the sample that were used in the econometric analysis to account for such contingent factors.

TAB 1 – Description and summary statistics of the variables used in the econometric analyses.

Variable	Description	Mean	Median	St. dev	1%	99%
SIZE i,t	Log of the total assets of company i in year t (based on the perpetual inventory method)	14.30	14.33	1.38	10.97	17.70
INTANG i,t	Ratio of the book values of intangible assets to tangible assets for company i in year t	0.15	0.08	0.19	0	0.85
LEV i,t	book value of debt / (book value of debt + book value of equity)	0.68	0.72	0.20	0.17	0.98
ROE i,t	Net income / book value of equity	0.32	0.04	0.6	-1.59	0.73
VERT_INT i,t	value added/ turnover	0.28	0.28	3.30	0.05	0.68
DEBT_MAT i,t	Long term debt / total debt	0.13	0.08	0.15	0	0.61
EMPLOYEES	Number of employees	111	56	330	16	921

4.2 Transition Probability Matrixes on TFP growth rates

The following three tables report the results obtained for the persistence of TFP growth rates over time, using different discretisation criteria. In table 3 we have implemented the standard TPM approach by splitting the distribution of firm level TFP growth rates in tertiles. In the table we also report the standard errors of the related transition probabilities[5].

The data show that, during the observed years, the firms that were in the top tertile of TFP growth rates in their sector in year t-1 were, on average, again in the top tertile in year t with a probability of 54.04%. Overall, the data in Table 2 highlight the presence of strong persistence: the main diagonal terms are larger than 33%. The incidence of inter-temporal transition between the lowest and the highest tertiles is quite low in both directions, and is below 20%. The analysis was replicated by splitting the distributions into quartiles (see Table A1 in Annex A). Again the data confirmed the presence of non-negligible persistency patterns. As could be expected, inter-quantile mobility was higher for the intermediate intervals. This seems to highlight the presence within the sample of sub populations of firms than are capable of repeatedly outperforming their peers in terms of TFP growth. Results of a transition probability matrix in which we focus on smaller companies are shown in Table 3. This evidence confirms that persistence is in line with the patterns identified for the whole sample. This would seem to suggest that the persistence phenomenon cannot be attributed completely to the presence of different TFP trends in the sub samples of small and large companies in the dataset.

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[5] 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} .

Table 2. Transition Probability Matrix on the tertiles of the sectoral distribution TFP growth rates for all the years and all the companies.

	High Growth t	Mid Growth t	Low Growth t
High Growth t-1	0.5404 (0.0041)	0.2776 (0.0035)	0.172 (0.0031)
Mid Growth t-1	0.2911 (0.0038)	0.4232 (0.0041)	0.2857 (0.0038)
Low Growth t-1	0.1807 (0.0032)	0.2826 (0.0038)	0.5367 (0.0042)

Table 3. Transition Probability Matrix on the tertiles of the sectoral distribution TFP growth rates for all the years and the companies with less than 50 employees.

	High Growth t	Mid Growth t	Low Growth t
High Growth t-1	0.0538??? (0.0028)	0.2827 (0.0057)	0.1793 (0.0048)
Mid Growth t-1	0.3018 (0.0061)	0.4033 (0.0064)	0.2948 (0.0060)
Low Growth t-1	0.1873 (0.0050)	0.2853 (0.0057)	0.5274 (0.0064)

In the following Tables 4 and 5 we apply the MTPM approach with the splitting of the transition probability matrixes into different sub-periods and regions. In tables 4 and 5 we also report a global index of persistence (G) which is defined as follows:

$$G = \left(N_{HighGrowth(t),HighGrowth(t-1)} + N_{MidGrowth(t),MidGrowth(t-1)} + N_{LowGrowth(t),LowGrowth(t-1)}\right) / N_{tot(t-1)} \qquad (5)$$

Higher values of G indicate an overall average higher stability of companies within each of the tertiles of the distribution of the TFP growth rates. The MTPM splitting approach has the aim of capturing the presence of divergences in persistency patterns of TFP growth rates due to the influence of the external environment. In particular, we claim that the knowledge intensity of the local context may be relevant in shaping differentiated patterns of persistence in productivity growth. For this purpose we have split Italian regions into HighR&D and LowR&D regions, on the basis of the average aggregated R&D expenditures during the observed years. High R&D regions fall into the top 33% of the distribution of regions in terms of Gross R&D Expenditures/GDP. Moreover, the macroeconomic context can play an important role in influencing the productivity performance of firms and their reactions to changing economic conditions in terms of contingent behaviour, and strategic decisions may differ. Considering that the time span adopted for the analysis can be conveniently divided into two sub-periods, which identify an upward economic cycle (until 2001) and a downward cycle (after 2001) in Italy, we split the TPMs in order to eventually detect any eventual differences in persistency dynamics across the two groups of regions and the two sub-periods. The implementation of MTPM, with the estimation of two different TPMs for two subperiods, allows us to see whether the observed aggregate persistency patterns are the averaged outcome of processes with peculiar trends over different regions and time. The difference between the results of the two TPM when and if statistically significant is a reliable clue that contingent changes have occurred over the process, affecting its dynamics.

Table 4. Multiple Transition Probability Matrix on tertiles of the sectoral distribution TFP growth rates. The sample is restricted to companies located in High-R&D regions. A comparison between two TPMs before and after year 2001.

Before year 2001

	High Growth t	Mid Growth t	Low Growth t	G Index
High Growth t-1	0.4984 (0.0095)	0.3009 (0.0087)	0.2007 (0.0076)	
Mid Growth t-1	0.2724 (0.0084)	0.4098 (0.00937)	0.3178 (0.0088)	0.543
Low Growth t-1	0.1837 (0.0074)	0.2899 (0.0087)	0.5264 (0.0095)	

After year 2001

	High Growth	Mid Growth	Low Growth	G Index
High Growth t-1	0.5642 (0.0068)	0.2829 (0.0062)	0.153 (0.0049)	
Mid Growth t-1	0.2843 (0.0060)	0.448 (0.0066)	0.2677 (0.0059)	0.656
Low Growth t-1	0.1796 (0.0051)	0.2785 (0.0059)	0.5419 (0.0066)	

Table 5. Multiple Transition Probability Matrixes on tertiles of the sectoral distribution TFP growth rates. Sample restricted to companies located in Low-R&D regions. A comparison of two TPMs before and after year 2001.

Before year 2001

	High Growth t	Mid Growth t	Low Growth t	G Index
High Growth t-1	0.5483 (0.0110)	0.2816 (0.0099)	0.1701 (0.0083)	
Mid Growth t-1	0.3404 (0.0108)	0.4016 (0.0112)	0.258 (0.0100)	0.527
Low Growth t-1	0.2067 (0.0092)	0.2998 (0.0104)	0.4935 (0.0114)	

After year 2001

	High Growth t	Mid Growth t	Low Growth t	G Index
High Growth t-1	0.5344 (0.0076)	0.2879 (0.0069)	0.1777 (0.0058)	
Mid Growth t-1	0.2901 (0.0074)	0.4072 (0.0080)	0.3027 (0.0075)	0.663
Low Growth t-1	0.1665 (0.0061)	0.2745 (0.0073)	0.559 (0.0081)	

The results of the MTPM show that there are significant differences between the two subperiods. A single probability matrix would have absorbed the differences with averaging effects that hide the significant effects of processes that take place along the process. The data reveal for both of the regional samples an increase in the G index after 2001. However, in the case of the HighR&D regions this increase is explained above all by the significant increase in the persistency of outperforming companies (i.e. those in the first tertile of TFP growth rates distribution), while an opposite trend can be observed for the LowR&D regions. When interpreting these results, it is fundamental to consider that companies that start with lower TFP levels are more likely to exhibit higher

TFP growth rates. This aspect could be relevant in explaining the high level of stability of outperforming companies in LowR&D regions before 2001, which might be related to firms starting with lower TFP levels and taking advantage of the macroeconomic expansion, that occurred until 2001. The inversion of the economic cycle has powerful effects: firms belonging to the HighR&D regions seem to be more capable of sustaining persistently higher levels of productivity growth. One possible interpretation of this result is that in this economic phase the dominating effect could be related to the best companies that react to the changed economic context and which strategically invest in innovative activities to sustain persistently higher TFP gains.

4.3 Econometric Analysis

4.3.1 Modelling structure

The previous descriptive evidence clearly calls for a more detailed analysis of the actual underlying dynamics and of its driving factors. In order to analyze the persistence of TFP growth rates along the analyzed periods we have constructed a time varying dummy variable that equals one in period t if a company shows a TFP growth rate that falls within the top X% of the distribution of ΔTFP for all the companies in the same sector. We apply a dynamic discrete choice model in which such a variable is regressed against its past realization and a set of appropriate controls. We carry out a sensitivity analysis to investigate whether, and to what extent, the results are related to the selected X% threshold.

The observed persistence may be due to true state dependence or permanent unobserved heterogeneity across the analysed companies. From a theoretical perspective, if the source of persistence is due to permanent unobserved heterogeneity, individuals show higher propensity to make a decision, but there is no effect of previous choices on current utility and past experience has no behavioural effect (Heckman, 1981). Hence, in order to estimate true state persistence, it is important to capture the variance of the state indicator which explained by both the structural characteristics of the firms and by contingent, time-varying observable factors and then to analyse whether its past values still have a significant effect.

This research strategy and the ensuing econometric evidence can explain whether the non-ergodic dynamics of the process can be considered:

a) path dependent, if both the contingent time-varying factors that occur along the process and the state of the process at time t-1 show a significant effect on the current realisation of the process, while the initial conditions show no effect.

b) past dependent, if the current realisation of the process is only affected by the initial conditions, while the contingent time-varying factors that occur along the process do not exert any significant effects.

The baseline specification for a dynamic discrete response model is the following:

$$y_{it}^* = \gamma y_{it-1} + \beta x_{it} + u_i + \varepsilon_{it} \tag{6}$$

where y_{it} (with possible values 0,1) is the state indicator (i.e. indicating whether a firm is in the top X% of the TFP growth rate distribution in its sector in year t):

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 to the error term would give raise to biased estimates of the autoregressive parameter γ that represents the measure of persistence. Two different approaches can be adopted to handle such initial condition problem: Heckman (1981) suggests 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 the present empirical analysis we have applied the latter approach. In particular, we follow the methodology applied by Peters (2009) that priveds a simplification of the Wooldridge method. It uses 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:

$$u_i = \alpha_0 + \alpha_1 y_{i0} + \alpha_2 \bar{x}_i + c_i \tag{7}$$

where:

$$\bar{x}_i = T^{-1} \sum_{t=1}^{T} x_{it} \tag{8}$$

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

$$P(y_{it} = 1 \mid y_{i0}, ..., y_{it-1}, x_i, \bar{x}_i, c_i) = \phi(\gamma y_{it-1} + \beta x_{it} + \alpha_0 + \alpha_1 y_{i0} + \alpha_2 \bar{x}_i + c_i) \tag{9}$$

This methodology has the advantage of being less restrictive on exogeneity assumptions than the Heckman's approach. The method consists in estimating a dynamic random effect probit model in which the regressors include a dummy which represents the initial realization of the dependent variable and the time average of those covariates that are expected to be correlated to the individual effect. As previously mentioned, in order to identify true state persistence, it is necessary to account for the time varying firm-level characteristics, which are expected to be correlated to the observed outcome of the dichotomous dependent variable, and to control for the external context in which firms operate. Hence, we proceed by adding controls that can have an impact on productivity growth rates. This research strategy was motivated by the willingness to expand the discourse on the persistence of productivity growth rates beyond structural variables (e.g. sector and size of the firms) and to better account for the impact of the contingent factors that influence persistence along the process.

The contingent factors that should capture the path dependence nature of the dynamics are firm-level characteristics (including managerial decisions) and the characteristics of the external context.

As far as the firm-level characteristics that are likely to affect TFP growth are concerned, firm size (SIZE) and an indicator of firm profitability (ROE)[6] were used. An indicator of R&D efforts (INTANG), an indicator of vertical integration along the value chain (VERT_INT), an index of capital structure composition (LEV) and an indicator of debt maturity (DEBT_MAT) were used for the managerial variables.

The intangible assets intensity is expected to capture the effort of a firm to build innovative competences by means of both in-house R&D and external expenditures. While, in principle, the capital structure should have a neutral or non significant effect, it is here claimed that a higher incidence of long-term debt can be associated with the willingness of the managers to adopt a more long-term investment strategy. Since structural innovation investments require a stable commitment it is expected that sustained superior performances in TFP growth rates will be observed for those firms that have longer debt maturity. This, in turn, is a signal that such firms have made significant investments in long termed infrastructures. As far as the expected effect of the vertical integration indicator is concerned, we claim that lower values can be attributed to the willingness of focussing on those segments of the value chain that are characterised by higher value added. Hence, a negative relationship with TFP growth rates can be expected. This intuition is particularly relevant given that the sample is composed of manufacturing companies, that operate to a large extent in traditional sectors, and that during the observed years have carried out significant restructuring outsourcing of the production activities. All time varying firm-specific factors have been used in the model specifications with a 3 year lag. In the analysis we take into account also the evolution of the macroeconomic context. The sample of companies observed for the entire period

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6 The empirical evidence on the relationship between profitability measures and productivity is mixed, even when taking into account operative profitability (ROI or ROA). In general, the identification of linear effects appears to be difficult (See Antonelli and Scellato (2011) for a discussion).

(1996-2005) and has been split into two sub-periods, before and after 2001. This year was chosen because it identified a major contingent event that represented a turning point in the economic cycle during the period in which firms were observed. Moreover, it has the advantage of being in the middle of the panel, therefore problems of comparability related to large differences in the sample dimensions have been avoided. Finally, following the approach adopted for the MTPM we also split the sample between HighR&D and LowR&D regions in order to identify different trends of persistence in time between the two groups.

4.3.2 Results

In the following tables we show the results of different model specifications for the evaluation of persistence along time of TFP growth rates. In table 7 we adopt a threshold equal to the top 33% in order to identify the best performing firms in each time period. Model I is based on a standard random effects dynamic probit model while in model II we account for potential endogeneity of the lagged dependent variable[7]. Results confirm the summary evidence reported in the previous TPMs and indicate the presence of substantial persistence. Being in the top tertile of the distribution of TFP growth rates in year t-1 has a positive and largely significant impact on the likelihood of the firm still being in the top 33% in year t, with a marginal effect at means of about 30%. Such effect also holds after accounting for different time-varying controls which were inserted into the model specification at the beginning of the period over which the TFP growth rate is calculated[8].

The results for the covariates provide interesting insights that can be used to qualify such persistence. What is relevant in the analytical framework is that even after accounting for firm level time varying factors, there is still a significant impact of the lagged dependent variable. This implies that the persistence detected in the descriptive analysis is not spurious. Moreover, the estimated relevance of contingent factors allows one to exclude the ergodic nature of the process under scrutiny, while confirming its path dependent nature. The initial observation of the dependent variable ($HighGrowth_{t=0}$) has a negative effect but with a smaller marginal effect than the lagged dependent variable ($HighGrowth_{t-1}$). This evidence is sensible and suggests the presence within the observed dynamic process also of a component leading to a drift towards the mean[9].

With respect to the analysis of the contingent factors, as expected, size has a positive and significant effect in all model specifications. Moreover the strategies pursued by companies appear to have a significant effect on persistence dynamics. In this respect, the negative and significant effect of the vertical integration can easily be interpreted. Those companies that have reduced their vertical integration on average had a significantly higher likelihood of being among the best performers in terms of TFP

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7 As a robustness check of the results we have also run a set of model specifications using different thresholds of TFP growth rates (see Table A2 in Annex A). In particular we have chosen a more restrictive threshold: the top 15% of the distribution of TFP growth rates. Results confirm the presence of persistency patterns. The marginal effect for the lagged binary indicator (HighGrowtht-1) equals 0.266.

8 We have also tested different specifications for the growth rate of TFP, using both a two year and a four year interval. Results have not been affected.

growth rates. This evidence confirms that a managerial strategy that favours a process of specialization on those activities that are characterized by higher value added levels enhances the possibility of obtaining long lasting outperformance in productivity growth.

The variable related to debt management seem to highlight how those companies that have been able to finance long term investments through credit channels on average show higher TFP growth rates. This might mean that this subsample of companies is less financially constrained and does not have to rely solely on internal cash flows to finance growth and productivity enhancing assets. The summary statistics from the sample in fact reveal that a relevant share of companies has a very limited incidence of long term debt, meaning that these companies implicitly use (or are forced to use) external financial sources with a maturity of less than a year to support assets that are defined in the long run. While in this analytical setting it is not possible to assess whether such apparently irrational behavior is determined totally by external constraints (i.e. inefficiency of the credit markets), the data still provide a clear indication of the non trivial effects of the sources of finance.

It is necessary to adopt caution when interpreting the results obtained for the variable capturing intangible intensity. We find a positive effect which is highly significant in model I, where we do not account for endogeneity, and this could point to a relevance of management strategies aiming at leveraging dynamic capabilities and R&D activities to sustain superior productivity performance. However, this variable it is no longer significant in model II in which we account for endogeneity. This might reflect that the intensity of intangible assets is mostly a firm-specific factor but also, as will be shown, that composition effects, in terms of location and time, are relevant. Finally, we have identified a not statistically significant effect of past levels of Return on Equity on subsequent TFP growth rates. This might be due to the fact that, in the present sample, companies within an industry tend to differ more in terms of operational efficiency than ROE along time. Hence, the overall evidence indicates that time-varying decisions taken by firms have both a direct impact on the current productivity growth rates and additional effects on the subsequent growth rates, due to the hysteretic property of the analyzed dynamic process.

Table 6. Dynamic probit model on the persistence of the TFP growth rates. The dependent variable ($HighGrowth_t$) is equal to 1 in year t for firm i if the corresponding growth rate of TFP falls into the first tertile of the related sectoral distribution of the TFP growth rates. Model II implements the Wooldrige (2005) methodology to account for the endogeneity of the initial observation. Marginal effects are reported.

Models	I	II
HighGrowth $_{t-1}$	0.300***	0.303***
	(0.005)	(0.005)
SIZE $_{t-3}$	0.012***	0.120***
	(0.002)	(0.006)
ROE $_{t-3}$	0.001	0.001
	(0.001)	(0.001)
INTANG $_{t-3}$	0.082***	0.039
	(0.014)	(0.024)
VERT_INT $_{t-3}$	-0.304***	-0.317***
	(0.018)	(0.018)
LEVERAGE $_{t-3}$	0.003	0.004
	(0.004)	(0.004)
DEBT_MAT $_{t-3}$	0.068***	0.120***
	(0.017)	(0.025)
AVGSIZE		-0.116***
		(0.006)
AVGROE		0.001
		(0.001)
AVGINTANG		0.050*
		(0.029)
AVGVERT_INT		0.009**
		(0.004)
AVGLEVERAGE		0.000
		(0.000)
AVGDEBT_MAT		-0.093***
		(0.034)
HighGrowth $_{t0}$		-0.027***
		(0.005)
REG Dummies	Yes	Yes
Num Obs	42,120	42,120
Wald Chi-sq	4142.2***	4479.4***
LogLik	-24841.061	-24632.811

*Significance levels: * 90% **95% ***99%*

In order to take into account external effects, regressions were run for different sub-samples of companies belonging to the HighR&D and LowR&D regions during the expansion and contraction phases of the business cycle. The results reported in Table 7 confirm the relevance of the external context and show differentiated dynamics of persistence across the regions and in time. In particular, the increase after the year 2001 in the magnitude of the coefficient associated with the lagged dependent variable is higher for HighR&D regions than for LowR&D. This confirms the descriptive evidence presented in the previous section. In particular, it is shown that the firms in HighR&D regions capable of sustaining superior performances in TFP growth in the downturn are those that are committed to long term investments and which are leveraging dynamic capabilities by investing in intangible assets. On the contrary, in the LowR&D regions, with the inversion of the economic cycle, the external environment does not seem to support the role of intangible assets in explaining superior productivity performances.

Table 7. Dynamic probit model on the persistence of the TFP growth rates for subsamples. The Ddependent variable (HighGrowth$_t$) equals 1 in year t for firm i if the corresponding growth rate of TFP falls in the first tertile of the related sectoral distribution of TFP growth rates. All the models account for endogeneity. Marginal effects are reported.

Samples	HighR&D before 2001	HighR&D after 2001	LowR&D before 2001	LowR&D after 2001
Models	I	II	III	IV
HighGrowth $_{t-1}$	0.242***	0.331***	0.281***	0.301***
	(0.015)	(0.008)	(0.018)	(0.009)
SIZE $_{t-3}$	0.150***	0.142***	0.156***	0.073***
	(0.012)	(0.011)	(0.016)	(0.013)
ROE $_{t-3}$	-0.038***	0.001	0.000	0.001
	(0.008)	(0.001)	(0.001)	(0.002)
INTANG $_{t-3}$	0.031	0.077**	0.166**	-0.020
	(0.052)	(0.039)	(0.068)	(0.045)
VERT_INT $_{t-3}$	-1.511***	-0.373***	-0.283***	-0.311***
	(0.099)	(0.032)	(0.050)	(0.037)
LEVERAGE $_{t-3}$	-0.060**	0.007	0.000	0.023
	(0.026)	(0.009)	(0.015)	(0.020)
DEBT_MAT $_{t-3}$	0.067	0.107***	0.107	0.137***
	(0.053)	(0.041)	(0.066)	(0.047)
AVGSIZE	-0.144***	-0.140***	-0.153***	-0.063***
	(0.013)	(0.011)	(0.017)	(0.013)
AVGROE	-0.000	0.001	0.007	0.005
	(0.001)	(0.001)	(0.005)	(0.003)
AVGINTANG	-0.009	0.049	-0.112	0.113**
	(0.060)	(0.048)	(0.079)	(0.056)
AVGVERT_INT	1.349***	0.004	0.051	0.067***
	(0.106)	(0.004)	(0.033)	(0.019)
AVGLEVERAGE	-0.000	0.000	0.001	0.000
	(0.000)	(0.000)	(0.001)	(0.000)
AVGDEBT_MAT	-0.064	-0.088	-0.032	-0.118*
	(0.074)	(0.055)	(0.093)	(0.067)
HighGrowth $_{t0}$	0.006	-0.021***	-0.038**	-0.025***
	(0.014)	(0.008)	(0.018)	(0.009)
REG Dummies	YES	YES	YES	YES
Num Obs	8196	16392	5844	11688
Wald Chi-sq	916.9***	1996.1***	598.7***	1237.3***
LogLik	-4624.559	-9432.480	-3526.558	-6855.423

*Significance levels: * 90% **95% ***99%*

5. CONCLUSIONS

This paper provides empirical evidence on the path dependent persistence of productivity growth. The analysis of the persistence of total factor productivity growth, rather than of R&D expenditures and patents, makes it possible to consider the effects not only of the persistence of the introduction of innovations, but also of their timely and appropriate adoption and imitation. The selective adoption of new products, introduced upstream in factor markets by suppliers, and imitation of new products introduced in the same or adjacent product markets do have important effects on the increase of the general levels of efficiency of firm. From this viewpoint, this paper provides an original investigation of the persistence of the broad range of innovative activities, including adoption and imitation, next to the sheer introduction, as the results of activities that are characterized by high levels of knowledge intensity. The use of Multiple Transition Probability Matrixes (MTPMs) consisting in the splitting of standard TPM along the stretch of time under consideration and a comparison between the results of the two TPMs has provided interesting results. These results confirm that the MTPM methodology is an important tool that deserves broader use in the analysis of non-ergodic processes as it enables to discriminate between past and path dependent dynamics. The subsequent econometric analysis of firm level TFP for a sample of 7020 Italian manufacturing companies, observed during years 1996-2005, has shown that firms that have been able to improve the general efficiency of their production process at time t are more likely to sustain above average performance in the following periods of time, than firms with lower past rates of TFP growth. Such a persistence turned out to be path dependent, rather than past dependent, as it is shaped by a number of complementary and contingent factors that affect locally the dynamics of the process.

The identification of the path dependent character of persistence in productivity growth helps one to understand and appreciate the variety of results in the previous literature. The differences in the results of an increasing array of empirical investigations can be interpreted as follows: innovative activities have indeed potential hysteretic effects that only become actual persistence in productivity growth when a number of complementary and contingent factors concur to making the process actually non-ergodic. At each point in time, the probability of introducing, adopting and imitating further innovations and of outperforming competitors in TFP growth is in fact affected by the sequence of results in the past but is also conditioned by the actual levels of internal dynamic capabilities of each firm to accumulate and exploit technological knowledge and human capital.

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ANNEX A – Robustness checks

Table A1 Transition Probability Matrix on quartiles of the sectoral distribution TFP growth rates. All years and companies.

	High Growth t	Mid-High Growth t	Mid-Low Growth t	Low Growth t
High Growth t-1	0.4748 (0.0048)	0.2496 (0.0042)	0.1617 (0.0035)	0.1134 (0.0030)
Mid-High Growth t-1	0.2472 (0.0041)	0.3343 (0.0045)	0.2585 (0.0042)	0.1595 (0.0035)
Mid-Low Growth t-1	0.1576 (0.0035)	0.2624 (0.0042)	0.3356 (0.0045)	0.2442 (0.0041)
Low Growth t-1	0.1169 (0.0031)	0.1563 (0.0035)	0.2471 (0.0042)	0.4795 (0.0048)

Table A2 – Dynamic probit model on the persistence of TFP growth rates. Dependent variable ($HighGrowth_t$) equals 1 in year t for firm i if the corresponding growth rate of TFP falls in the first 15% of the related sectoral distribution of TFP growth rates. Model II implements the Wooldrige (2005) methodology to account for the endogeneity of initial observation. Marginal effects are reported.

Models	I	II
HighGrowth $_{t-1}$	0.266***	0.265***
	(0.006)	(0.007)
SIZE $_{t-3}$	0.007***	0.073***
	(0.001)	(0.004)
ROE $_{t-3}$	0.000	0.000
	(0.000)	(0.000)
INTANG $_{t-3}$	0.070***	0.014
	(0.010)	(0.017)
VERT_INT $_{t-3}$	-0.269***	-0.273***
	(0.013)	(0.014)
LEVERAGE $_{t-3}$	0.001	0.001
	(0.001)	(0.001)
DEBT_MAT $_{t-3}$	0.038***	0.096***
	(0.012)	(0.017)
AVGSIZE		-0.069***
		(0.005)
AVGROE		0.001*
		(0.000)
AVGINTANG		0.071***
		(0.020)
AVGVERT_INT		0.004*
		(0.003)
AVGLEVERAGE		0.000
		(0.000)
AVGDEBT_MAT		-0.110***
		(0.025)
HighGrowth $_{t0}$		-0.010**
		(0.005)
REG Dummies	Yes	Yes
Num Obs	42120	42120
Wald Chi-sq	3136.6***	3397.3***
LogLik	-16143.7	-15980.4

*Significance levels: * 90% **95% ***99*