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Technological regimes and sectoral differences in productivity growth

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Abstract

The paper explores a novel extension of the R&D-productivity literature. It puts forward an empirical model where sectoral productivity growth is related to the characteristics of technological regimes and a set of other industry-specific economic features. The model is estimated on a cross-section of manufacturing industries in nine European countries for the period 1996-2001. The econometric results provide basic support for most of the hypotheses put forward by the model. They show, in particular, that sectoral differences in productivity growth in Europe are related to cross-industry differences in terms of the following main factors: (1) appropriability conditions; (2) levels of technological opportunities; (3) education and skill levels; (4) the degree of openness to foreign competition; (5) the size of the market.

1. Introduction

Why do growth rates differ across industries? Why do some sectors increase their share in the overall national production over time, while others gradually decline? And to what extent does innovation determine sectoral differences in productivity growth? Innovation scholars have extensively investigated these questions in the last few decades, greatly inspired by Schumpeter's seminal work (1934 and 1939) on the importance of innovation for the process of structural change and economic dynamics.

There now exists a substantial empirical literature on sectoral differences in economic growth, and particularly on the impact of R&D activities on the dynamics of productivity. These works, recently surveyed by Los and Verspagen (2004), have mainly focused on the direct and indirect effects of R&D expenditures on sectoral productivity growth, and generally found a positive impact of R&D expenditures and R&D spillovers on structural change. These econometric studies have greatly improved our understanding of the determinants of sectoral differences in productivity growth.

However, when we compare the findings of this literature to those emerging from the increasing number of contributions on sectoral patterns of innovation in evolutionary economics (Pavitt, 1984; Dosi, 1988; Malerba, 2002), there appears to be ground for further improvements in the analysis of the structural change process. In evolutionary economics, differences in growth rates across industries may not simply be related to the stock of R&D expenditures and the related spillovers, but they rather depend on a more complex set of structural factors and sector-specific techno-economic conditions.

Instead of regarding the R&D stock as an exogenous production factor, innovation scholars have shown that R&D is, in turn, the outcome of other technological and market conditions that interact in the innovative process. A rich empirical literature has pointed out that R&D is the complex outcome of the interaction of industry-specific characteristics in a given market context (Cohen and Levinthal, 1989 and 1990). It has been shown, in particular, that R&D expenditures greatly vary across industries, and that such differences may be explained by differences in the levels and sources of technological opportunities, as well as by different appropriability, cumulativeness and demand conditions. Thus, it seems natural to extend the investigation of the R&D-productivity link by exploring the relationships between the sector-specific determinants of R&D expenditures and the growth of sectoral productivity. This is the novel extension of the R&D-productivity literature that the present paper will explore.

Such an extension is investigated by focusing on the concept of *technological regime*, which may be defined as the technological environment in which innovative and learning activities take place within each sector of the economy (Nelson and Winter, 1982; Winter, 1984). Recent evolutionary applied studies have shown that the characteristics of technological regimes well explain differences in the performance of manufacturing industries, particularly in terms of international technological performance (Malerba and Orsenigo, 1995 and 1996; Malerba and Montobbio, 2003) and competitiveness and trade dynamics (Laursen, 1999; Park and Lee, 2006; Laursen and Meliciani, 2000 and 2002). The present paper aims at contributing to this ongoing research by investigating the relationships between technological regimes and sectoral productivity growth.

The paper puts forward an empirical model where the growth of industrial sectors is conceptualised as the outcome of the interplay of a complex set of factors. The first set of factors refers to the characteristics defining sectoral technological regimes, namely appropriability and cumulativeness conditions, and levels and sources of technological opportunities. A second set of characteristics relates to some relevant industry-specific economic features, such as education and skill levels, the degree of openness to foreign competition, and the size of the market. In a nutshell, the model emphasizes the need to consider both technological and economic factors in the explanation of productivity differences, and it investigates the existence of interactions among them.

This empirical model is estimated on a cross-section of 22 manufacturing industries in nine European countries for the period 1996-2001. The data are taken from three different sources. Informations on the economic characteristics of each sector (e.g. labour productivity, exports) are taken from the OECD-STAN database. Data on education and skill levels of industrial sectors are obtained from Eurostat's Labour Force Survey. Indicators of innovative activities and sectoral technological regimes are calculated from the CIS-SIEPI database, a new source that contains data from the Second Community Innovation Survey on the innovative activity of European manufacturing industries (2-digit level). The results of the estimations provide basic support for the model, and show the relevance of both technological and economic factors for explaining sectoral differences in productivity growth.

The paper is organized as follows. Section 2 briefly reviews the mainstream empirical literature on R&D spillovers and productivity growth. Section 3 shifts the focus to evolutionary economics, and it presents the empirical model and its main hypotheses. Section 4 points out the data and the indicators used in the empirical study. Section 5 presents the results of the regression analysis. Section 6 concludes the paper by summing up the main results and discussing some of its limitations and the possible future extensions of this line of research.

2. The mainstream view: R&D, spillovers and productivity growth

About two decades ago, the first contributions within the new growth theory tradition pointed out the important role of increasing returns for the growth process, and introduced this idea into a formal endogenous growth framework. The first models argued that investments in physical and human capital may generate externalities, increasing returns and, hence, persistent growth differences across countries (Romer, 1986; Lucas, 1988; Azariadis and Drazen, 1990). Subsequently, a second generation of models focused on the role of the R&D sector and the endogenous nature of the growth process. In the models of Romer (1990) and Aghion and Howitt (1992), the R&D sector produces new blueprints for the intermediate goods sector, and the expansion of the range of intermediate goods determines increasing returns and a scale effect on aggregate growth.

The idea that sectoral R&D and knowledge spillovers are important for growth and competitiveness originates from these innovation-based new growth models. The main underlying assumption is that knowledge is a non-rival and (partly) non-excludable good, and that its public good characteristics lead to the existence of spillovers, increasing returns and endogenous growth.

These theoretical ideas raised new interesting questions for applied research. Do R&D and knowledge spillovers effectively lead to productivity growth, and how do industries differ in this respect? The empirical literature investigating the impact of R&D activities on sectoral differences in productivity growth is now large.[1] Typically, these contributions consist of econometric studies where the R&D stock (knowledge capital) is included as a production factor together with capital and labour in an extended Cobb-Douglas specification. It is however hard to obtain a good measure of the knowledge capital variable, and the perpetual inventory method that is frequently used to calculate the R&D stock presents some important problems, such as the difficulty to get an accurate estimate of the depreciation rate. The empirical strategy that it is typically used to overcome these problems is to estimate an econometric specification that relates the growth of total factor productivity (TFP) in each sector to its level of R&D expenditures (Nadiri, 1993).[2]

A large part of this literature focuses on the indirect contribution that R&D expenditures in a sector have on the growth of productivity in other industries, so-called R&D spillovers (Griliches, 1992). From a conceptual point of view, it is possible to distinguish between two different types of spillover effects (Griliches, 1979). *Rent spillovers* are those where there is a pecuniary exchange between the provider and the recipient of technology, such as in the case of a supplier that sells an intermediate input to a user. *Knowledge spillovers*, on the other hand, do not entail any contractual agreement or pecuniary exchange between provider and recipient, and arise because of the public good nature of knowledge. It is therefore this second type of spillovers that more closely corresponds to the idea underlying new growth models. The major channels through which knowledge spillovers affect the growth of productivity are all related to innovating firms' R&D capabilities: reverse engineering, the mobility of R&D employees, their participation to technical meetings and scientific conferences, and the exploitation of

[1] There exist several overviews of this empirical literature. Nadiri (1993) summarizes the main results of the major econometric works; Los and Verspagen (2004) review the various methodologies used in different strands of empirical analysis; and David et al. (2000) focus on the relationships between private and public R&D.

[2] This empirical method has not only been applied in the context of industry-level studies for a cross-section of economies, but also at the micro level by making use of firm-level data for individual countries. The greater availability of firm-level cross-sectional and longitudinal datasets has recently attracted the attention of many scholars in the field, and the study of R&D spillovers across firms does currently constitute the bulk of the empirical literature. Wieser (2005) presents a very comprehensive survey of this type of research focused on data, empirical methods and econometric results. Bartelsman and Doms (2000) do also discuss, in addition to R&D-related factors, other determinants of firms' productivity growth (e.g. exports, regulatory factors, etc.).

codified information available in the form of scientific journals and patents (Levin et al., 1987).

The conceptual distinction between rent and knowledge spillovers is important, although it is frequently not possible to separate the two categories in empirical analyses. The strategy followed by most contributions in this field is to weight the R&D expenditures of other sectors and to use it as a measure of intersectoral R&D spillovers. This is typically done in two ways. The first is to use transaction-based weights, such as inter-industry sales or investment flows, while the second is to construct measures of technological distance between industries. The former method closely corresponds to the concept of rent spillovers, whereas the latter implicitly focuses on knowledge spillovers.

The latter way to build up a measure of R&D spillovers has been followed by Jaffe (1986), who used as weights the distribution of patents across patent classes, and by Verspagen (1997a, 1997b), who used patent classifications and patent citations. These contributions, along with several others in this field, have generally found evidence of a positive influence of R&D spillovers on sectoral productivity growth. Using a different methodology, based on a growth accounting type of sectoral decomposition of TFP, ten Raa and Wolff (2000) found a similar result, and showed the importance of technological spillovers from high-tech sectors (e.g. computers and electronics) for the growth of TFP of the whole economy.

A second strand of research in the R&D spillovers literature has extended the analysis to the investigation of the nature, extent and impacts of *international* knowledge spillovers. This empirical research is inspired by a class of new growth models where sectoral R&D activities do not only sustain the dynamics of the domestic economy, but also have positive effects for the competitiveness of foreign countries.[3] In the models of Riviera-Batiz and Romer (1991) and Grossman and Helpman (1991), in particular, the R&D sector produces new blueprints that increase the variety of available intermediate inputs, and these positively affect the growth of foreign countries through cross-border trade and knowledge flows (representing channels of rent and knowledge spillovers respectively).

[3] For an overview of this type of new growth and new trade models, see Chui et al. (2002) and Darity and Davis (2005).

The major questions that these analytical models raise are therefore whether spillovers are really global, rather than national, in scope, and what the most effective channels of international diffusion are. Considering these issues, a set of recent empirical works have weighted R&D in other countries with imports, so to obtain a measure of foreign R&D acquired through imports of goods and services (see overview by Barba-Navaretti and Tarr, 2000). In particular, Coe and Helpman (1995), Eaton and Kortum (1996) and Coe et al. (1997) found that both domestic and international R&D spillovers have a positive effect on the growth of TFP at the aggregate level, and that the international diffusion of knowledge is a more relevant growth engine for small open economies than for large countries.

Verspagen (1997b), Dalum, Laursen and Verspagen (1999), Fagerberg and Verspagen (2000) and Keller (2000) performed a similar analysis at the sectoral level, and showed that both kinds of spillovers contribute to explain differences in productivity growth across industries. However, these works also pointed out that the relative importance of domestic vs. foreign R&D spillovers depends to a great extent on the econometric framework in which the analysis is undertaken. Foreign spillovers appear relatively more important when panel data are used, but much less relevant when the sample is cross-sectional in nature (Gittleman and Wolff, 1995).

On the whole, the huge empirical literature on the direct and indirect effects of R&D expenditures has significantly improved our understanding of the determinants of sectoral differences in productivity growth. However, this body of research raises one major question. Given that R&D activities constitute a major factor to sustain the economic performance of industries, what does, in turn, determine sectoral differences in R&D intensity? A large number of studies in industrial organization and, more recently, in the economics of innovation have pointed out that R&D activities differ markedly across sectors, and that these differences may be explained as the outcome of the interplay of a complex set of sector-specific characteristics (e.g. Levin et al., 1987). Among these characteristics, a great deal of attention has recently been devoted to the features that define the technological regimes of industrial sectors, namely the levels and sources of technological opportunities, and the conditions of appropriability, cumulativeness and demand that characterize each industry (Cohen and Levin, 1989).

Hence, productivity growth does not merely depend on the R&D intensity of each sector, but, first and foremost, on a complex set of structural characteristics that define the industry-specific opportunities, strategies and obstacles of innovative activities in different sectors of the economy. It seems thus natural to extend the investigation of the R&D-productivity link by exploring directly the relationships between the sector-specific determinants of R&D expenditures and the growth of sectoral productivity. This is the extension of the R&D-productivity literature that the following sections will explore.

3. An evolutionary model of sectoral productivity growth

Evolutionary economics conceives innovation as a paradigm-bounded, sector-specific and context-dependent activity.[4] The paradigmatic nature refers to the existence of dominant technological paradigms that create, in any given historical era, a set of opportunities and constraints for innovative activities (Nelson and Winter, 1982; Dosi, 1982; Freeman et al., 1982).

Industries, however, "differ significantly in the extent to which they can exploit the prevailing general natural trajectories, and these differences influence the rise and fall of different industries and technologies" (Nelson and Winter, 1977: 59). Thus, the paradigmatic nature of technological knowledge does not only explain the relatively ordered patterns that may be observed in each phase of long run growth at the aggregate level (Dosi, 1988), but also the inherent tendency towards qualitative change and transformations at the sectoral level. This accounts for the industry-specific nature of innovation, which naturally leads, in turn, to give emphasis to the systemic context in which the innovative process unfolds. In the evolutionary view, the impact of innovation on the economic performance of industries must therefore be analysed within a complex framework comprising both, the broader systemic context shaping innovative activities, and the sectoral specificities that characterize the creation and diffusion of knowledge.

[4] For a survey and discussion of the microfoundations of evolutionary growth theorizing, see the recent contributions of Becker (2004) and Winter (2006a) in this *Journal*. For a more general overview of the evolutionary economic paradigm and a comparison with the mainstream approach, see Castellacci (2006 and 2007).

Sectoral systems of innovation (Malerba, 2002 and 2005) differ along various dimensions, such as the institutional context shaping industrial innovative activities, the demand conditions providing opportunities and constraints for the commercialisation of new products and processes, and the sector-specific nature of learning processes, which are specific to a given technological environment.

A *technological regime* (Nelson and Winter, 1982; Winter, 1984) defines such a technological environment, i.e. the framework conditions in which firms' innovative activities take place. In each sector of the economy, some technological characteristics affect the direction and intensity of learning processes and the knowledge accumulation of economic agents. Extending previous empirical works in industrial organization (Cohen and Levin, 1989), recent evolutionary studies have in particular focused on four main aspects of sectoral technological regimes, namely technological opportunities, properties of the knowledge base, appropriability and cumulativeness conditions. The investigation of the nature and extent of cross-sectoral differences in terms of these factors has recently led to a surge of applied research. In particular, it has been shown that the characteristics of technological regimes may shed new light on three relevant aspects of the relationship between innovation and the economic performance of industries.

First, they may explain the existence of distinct patterns of market structure and industrial dynamics in different sectors of the economy. Most of the recent works in this field (Malerba and Orsenigo, 1995 and 1996; Breschi and Malerba, 1997; Breschi et al., 2000; Van Dijk, 2000) have focused on sectoral differences in terms of concentration of innovative activity, size of innovative firms, ease of entry in the market, turbulence or stability in the population of innovative firms. These evolutionary studies have argued that different technological regimes may explain the existence of the innovation patterns originally pointed out by Schumpeter (1934 and 1943). The first, the *Schumpeter Mark I*, is characterized by high ease of entry in the market, low concentration of innovative activity, and a turbulent population of new and old innovators with a significant role played by small firms. Creative destruction (Schumpeter, 1934) is the main feature of this regime (also defined 'entrepreneurial' or 'widening'). The second, the *Schumpeter Mark II* pattern, is characterized by high barriers to entry for new innovators, high concentration of innovative activity, and a stable population mainly formed by large and well-established firms. Creative accumulation (Schumpeter, 1943) is the distinctive feature of such a regime, also defined ‘routinized’ or ‘deepening’.

Secondly, it has been shown that different technological regimes have well-distinct impacts in terms of international technological performance. Malerba and Orsenigo (1996) and Malerba and Montobbio (2003) have recently demonstrated that technological opportunities, properties of the knowledge base, appropriability and cumulativeness conditions may explain the patters of international technological performance (e.g. measured by the revealed technological advantage in terms of patents) of different sectors in industrialized countries.

Thirdly, the characteristics of technological regimes have also been shown to have an impact in terms of competitiveness and trade performance. In fact, following the insights of technology-gap trade theory (Fagerberg, 1988; Dosi et al., 1990), recent empirical works have found that competitiveness and trade performance are greatly dependent on a range of technological variables, such as sectoral technological opportunities (Amable and Verspagen, 1995; Padoan, 1998; Laursen, 1999; Montobbio, 2003), cumulativeness conditions (Lee and Lim, 2001; Park and Lee, 2006) and (inter-sectoral) vertical linkages with the users and with the suppliers of new technologies (Fagerberg, 1995; Laursen and Meliciani, 2000 and 2002).

In sum, the increasing number of evolutionary studies on the nature and impacts of technological regimes points out that the economic performance of technological change in each sector depends to a great extent on the characteristics defining the technological environment in which learning activities take place. It is plausible to think, however, that the technological and trade performance of each sector in foreign markets is strictly linked to the dynamics of its labour productivity. Thus, the recent empirical findings outlined above suggest to investigate a new, still unexplored, link. The characteristics defining technological regimes may not only have an impact on sectoral patterns of technological specialization and trade performance, but, first and foremost, on the growth of labour productivity. It is precisely such a relationship, between technological regimes and sectoral productivity growth, that our model explores.

3.1 Model and hypotheses

Figure 1 presents a stylised view of an evolutionary model linking technological regimes to the growth of productivity of industrial sectors. As the diagram shows, the dynamics of productivity is conceptualised as the outcome of the interplay of a complex set of factors. In addition to the technology-related factors that are commonly considered in evolutionary studies, the model also considers a set of other industry-specific characteristics, such as sectoral education and skill levels, the degree of openness to foreign competition, and the size of the market. These structural characteristics, by interacting with sectoral technological regimes, do also play a relevant role to shape the dynamics of industrial growth. Let us point out more specifically the relevance of each factor and its expected impact on sectoral productivity growth.

< Figure 1 here >

3.1.1 Technological regimes

Appropriability conditions. These define the possibilities of appropriating the innovative rents by protecting innovations from imitation through a variety of means, such as patents, process secrecy and know-how, design and R&D know-how, and other non-technical means.[5] Regarding the relationship between the conditions of appropriability and the growth of productivity in each sector, the literature has previously identified two distinct mechanisms that may work in different directions (Cohen and Levin, 1989).

On the one hand, there is an *incentive effect*: when the rents coming from the introduction of new products and processes can be appropriated by innovating firms, these have a greater incentive to go on investing in innovative activities in the future (Cohen and Levinthal, 1989 and 1990). Thus, in sectors with stronger appropriability conditions, there is a greater incentive to invest in innovative activities and technological capabilities, with a possible positive impact on the growth of productivity over time.

[5] For a discussion of the concept of appropriability in the classical contributions of Schumpeter, Arrow and Teece, see Winter (2006b).

On the other hand, previous studies have pointed to the existence of an *efficiency effect*, which goes in the opposite direction. The efficiency effect is due to the fact that when appropriability conditions are lower, there is a greater scope for other firms in the same sector to imitate and to adopt the new technologies introduced by innovating firms (Cohen and Levin, 1989). Thus, in sectors with lower degrees of appropriability, there exists a greater potential for intra-industry knowledge diffusion, with a possible beneficial effect on the growth of productivity.

Considering together the two opposite effects, the impact of appropriability conditions on sectoral productivity growth is difficult to determine on a priori ground. It is negative (positive) if the efficiency effect has a stronger (weaker) impact on productivity growth than the incentive effect.[6]

Cumulativeness conditions. They represent the extent to which current innovative activity builds upon the experience, capabilities and results achieved by innovative firms in the past. The importance of cumulativeness at the firm level has recently been investigated by Malerba and Orsenigo (2000), Cefis and Orsenigo (2001) and Fai and Von Tunzelmann (2001). According to these contributions, firms improve their absorptive capacities, knowledge competencies and organizational capabilities cumulatively over time, and this is a fundamental characteristic of the innovative process. Cumulativeness conditions persistently differ across industries, thus affecting the intensity and direction of technological change in each sector.[7]

A possible link between cumulativeness and sectoral productivity growth was originally suggested by Nelson and Winter, according to which

[6] Dosi et al. (2006) and Dosi, Marengo and Pasquali (2006) have recently reviewed the main empirical results on the effects of patents and IPRs on innovation and performance. This effect has in some contributions been found to be negative (e.g. Klevorick et al., 1995; Cohen and Levinthal, 1989 and 1990), but the empirical evidence is on the whole still mixed and not conclusive.

[7] Besides cumulativeness at the firm-level, there exist other potential sources of cumulativeness (Malerba, 2002). One is at the technology-level, and it may arise because learning processes and dynamic increasing returns shape and constrain the development of a technological trajectory. The other is related to market feedbacks and demand conditions, given that the profits and productivity gains related to innovative results may be reinvested in technological activities in the future, thus activating a success-breeds-success cumulative causation mechanism.

> "the relationship between R&D expenditure and rate of productivity growth in an industry may depend on the character of technical advance in the industry – in particular, […] on whether technical change in the industry is cumulative in the sense that today's advances build on yesterday's" (Nelson and Winter, 1982, p. 351).

Based on this suggestion, our model puts forward the hypothesis that a greater degree of cumulativeness of innovative activities leads to a higher rate of growth of sectoral productivity.

Level of technological opportunities. This may be defined as the "likelihood of innovating for any given amount of money invested in search".[8] Opportunity levels can be very high in some technologically advanced and emerging sectors, and rather low in more traditional low-tech industries (Von Tunzelmann and Acha, 2005). Technological opportunities represent a crucial aspect of technological regimes, and are linked to the ability of industries to exploit the emergence and diffusion of new technological paradigms:

> "The fundamental determinants of observed rates of innovation in individual industries/technologies appear to be nested in levels of opportunities which each industry faces. 'Opportunities' capture, so to speak, the width, depth and richness of the sea in which incumbents and entrants go fishing for innovation. […] The 'rates of fishing' depends essentially on the size and richness of the sea" (Dosi, Marengo and Pasquali, 2006: 10-11).

Our model assumes that innovative activity is a primary source of sectoral growth, and that different levels of technological opportunities may therefore explain a consistent part of differences in productivity growth across industries. In fact,

> "one would expect the rates of performance improvement over time (e.g. productivity growth) to be positively correlated with the levels of technological opportunities. […] The rates at

[8] Such a definition was put forward by Breschi and Malerba (1997), Breschi et al. (2000), and Malerba (2002 and 2005). It focuses on the *level* of technological opportunity, and particularly on the relationship between input and output of innovative activity. Cohen and Levinthal (1990, p. 139) had previously proposed a similar definition, according to which technological opportunity is "how costly it is for the firm to achieve some normalized unit of technical advance in a given industry".

> which opportunities are actually exploited (in terms of new/better products and more efficient processes of production) by, at least, some firms, and the rates at which these new products and processes diffuse to other firms obviously affect also the rates of change of industrial performance over time – e.g., the rates of productivity growth" (Dosi, 1988, p.1160).

Thus, following Dosi's suggestion and consistent with an evolutionary paradigmatic view of the process of innovation and structural change, the model puts forward the hypothesis that sectors with higher levels of technological opportunities have higher rates of productivity growth over time.

External sources of opportunities. The exploitation of technological opportunities is however a complex and multifaceted process. Besides the mere level of opportunities, an important complementary aspect is represented by the external sources of technological opportunities (Cohen and Levinthal; 1989 and 1990; Breschi et al., 2000). These constitute technological opportunities that are external to the innovative firm, and that can therefore be exploited by collaborating and interacting with other actors in the sectoral system of innovation. Firms in different sectors greatly vary in terms of their *intensity of interaction* and propensity to collaborate with other organizations (Malerba and Montobbio, 2003), as well as in terms of the *direction of their external linkages* (Pavitt, 1984). Regarding the latter aspect, the innovation literature has pointed out the relevance of three different types of actors that innovative firms in different sectors systematically interact with.

The first is represented by the *users* of new technologies (downstream linkages). This type of interaction may affect the growth of sectoral productivity through two related channels. First, as observed by Fagerberg (1995, p. 245), "a stable user-producer relationship may be interpreted as an institution that reduces the costs – and increases the pace – of innovation and learning". Thus, strong user-producer interactions will not only have a beneficial effect on competitiveness and trade (the so called 'home-market' hypothesis[9]), but on the dynamics of labour productivity as well. Relatedly, the interactions between innovative firms and the users of the new technologies lead to flows

[9] See Fagerberg (1995) for a detailed discussion of the 'home-market' hypothesis, and for an empirical analysis of the relationship between user-producer interactions and trade performance.

of technological knowledge, i.e. inter-industry knowledge spillovers, which may enhance productivity for both producers and users (Cohen and Levinthal, 1989 and 1990; Laursen and Meliciani, 2002).

Secondly, interactions between innovative firms and the *science system* constitute an important external source of opportunities, particularly in some advanced industries where the process of knowledge creation is closely related to scientific advances (Mowery and Sampat, 2005). Seminal contributions have previously suggested a relationship between this type of interaction in the innovative process and the growth of productivity. According to Nelson and Winter (1977, p.60), “a key factor that differs across industries and that partly resolves the differential productivity puzzles is the strength of scientific understanding relevant to seeking improvements”. Cohen and Levin (1989), reporting the findings of Nelson (1982), point out that

> “strong science affects the cost of innovation by increasing the productivity of applied research […]. A strong science base narrows the set of research options and focuses attention on the most productive approaches. The consequence is that the research process is more efficient. There is less trial-and-error; fewer approaches need to be evaluated and pursued to achieve a given technological end. From this perspective, the contribution of science is that it provides a powerful heuristic to the search process associated with technological change” (Cohen and Levin, 1989, p. 1086).

Thirdly, the *suppliers* represent an important source of knowledge for innovative firms. This is particularly the case in some traditional and low-tech industries, where the innovative process is frequently based on the acquisition of advanced machinery and equipments embodying technological change that are supplied by upstream industries (Pavitt, 1984; Evangelista, 1999). Upstream linkages may therefore constitute for some sectors an important mechanism to introduce process innovation and productivity growth (Reichstein and Salter, 2006).

In sum, our model assumes that external sources of technological opportunities are relevant factors to explain sectoral differences in productivity growth. The mechanism that translates external sources of opportunities into productivity gains may however be closely related to the level of technological opportunities, given that external linkages are arguably a more effective channel of growth in those industries that are characterized by a dynamic environment and high levels of technological opportunities. In other words, our model assumes that it is the interaction between levels *and* sources of opportunities that plays a crucial role for the growth of sectoral productivity.

3.1.2 Other industry-specific characteristics

Education and skill levels. Human capital has for a long time been considered an important factor to explain economic growth. While the traditional mainstream approach was to consider it as an additional factor in an extended production function framework, the more recent literature has recognised the existence of important interactions between education levels and technological change (Benhabib and Spiegel, 1994; Galor and Weil, 2000; Galor, 2005). Some recent aggregate models, in particular, focus on the role of ability and individual workers' skills in times of rapid and disruptive technological change (Galor and Tsiddon, 1997; Galor and Moav, 2000; Acemoglu et al., 2002). A related strand of literature analyses the so-called skill-biased technological change hypothesis, according to which innovation tends to increase the demand for skilled workers over time.[10] In a nutshell, what these strands of research suggest is the existence of a dual relationship between human capital and innovation, where education levels support the creation of new knowledge and, in turn, innovative activities foster the demand for advanced capabilities and skilled labour.

In line with the mainstream emphasis on the role of education levels for growth and technical change, evolutionary studies have also pointed out the relevance of organizational skills, capabilities and competencies (Nelson and Winter, 1982, chapter 4; Malerba and Orsenigo, 2000). The importance of these for the dynamics of productivity does not only refer to the greater ability of well-educated workers to perform rapidly routine-based tasks, but also to their more advanced capability to recognise, imitate and

[10] In empirical analyses, the skill-biased technological change hypothesis has frequently been investigated by making use of firm-level data for selected countries, and only to a limited extent through industry-level data for a large sample of economies, arguably due to the limited availability of comparable data on education and skill levels for a large sample of countries (OECD, 1996; Machin and Van Reenen, 1998; Griffith et al., 2004). For a review and discussion of the empirical evidence on skilled-biased technological change, see Pianta (2005) and Piva et al. (2005).

use technological knowledge and external sources of opportunities, so-called absorptive capacity (Cohen and Levinthal, 1989).

Organizational skills do not only depend on the education levels previously acquired by the workers, but may also be continuously supported and upgraded by specific training activities undertaken by innovative firms in close connection with the introduction of technological change.[11] Tidd et al. (1997) point out three main reasons why training activities are important for innovative firms: (1) they provide workers with the specific technical skills that are needed to operate new equipments; (2) they act as a motivator for the employees, and induce them to accept and adapt to rapid and radical technological changes; (3) they strengthen their ability to learn, i.e. their learning-how-to-learn capabilities.

Based on the existing literature, our model argues that sectoral productivity growth may be sustained by both, the general level of education previously acquired by the firms' employees as well as the more specific technical and organizational skills that are continuously developed by means of training activities carried out by innovative enterprises.

Degree of openness. Mainstream economic theory points out the existence of a positive relationship between the degree of openness of each sector and its growth performance. The reason is twofold. First, openness to foreign competition favours the development of economies of specialization that enhance sectoral productivity growth (Rivera-Batiz and Romer, 1991). Secondly, the acquisition of embodied and disembodied knowledge from foreign advanced industries through trade and FDI is an important source of international knowledge spillovers (Grossman and Helpman, 1991; Barba-Navaretti and Tarr, 2000).

Innovation theory and evolutionary approaches would however suggest to refine this hypothesis by looking at the interactions between openness conditions and technological opportunities. In fact, technology-gap studies have shown that technological opportunities represent a key factor to sustain the export performance and international competitiveness of domestic industries (e.g. Fagerberg, 1988; Laursen, 1999). In sectors

[11] Krueger and Kumar (2004) points out the existence of a different educational focus between US and Europe, where the educational system in European countries more frequently focuses on the development of specific skills rather than on general education.

with high opportunities, we may expect industries to develop competitive advantages in the long run, to have a better trade performance and, consequently, to achieve a more dynamic growth of productivity. The two aspects, the exploitation of new technological opportunities and the export performance of industries are closely related to each other, and the interaction among them may therefore be expected to sustain the dynamics of sectoral productivity.

However, this is admittedly a long-term argument, and in a shorter time horizon it would be reasonable to expect that new technological opportunities may be exploited in the home market first, where it is easier to introduce and commercialise new products and processes, before facing tougher competition in the international arena. Therefore, the effect of the interaction between technological opportunities and export on the growth of sectoral productivity is not easy to determine on a priori ground, and it will depend on the extent to which new opportunities are transformed into innovations that may be competitive in foreign markets.

Market size. Economic theory indicates the existence of a positive relationship linking the size of the market to the productivity growth performance. The first reason for this is of course rooted in the classical contributions of Adam Smith, which originally suggested that the deepening of the market and the related increasing division of labour lead to specialization effects, which constitute a crucial source of dynamics in the economic system. This argument was later refined by other classical authors such as Kaldor and Myrdal, who pointed out the existence of a process of cumulative causation based on the dynamic interactions between productivity and demand growth, where the growth of the latter sustains productivity gains though dynamic economies of scale and learning by doing mechanisms. Relatedly, a second reason for expecting a positive link between market size and productivity growth has more recently been put forward by new growth theory models, which argue that the size of the R&D sector is an important factor of endogenous growth for the whole economy (Romer, 1990; see section 2).

Innovation theory would again suggest to complement this basic hypothesis by considering the interactions between market size and technological opportunities. The reason is that in large sectors there is greater scope for intra-industry knowledge diffusion, trial-and-errors, adaptation, incremental improvements and learning by doing mechanisms linked to the introduction and commercialisation of new technologies. To the extent that there are new technological opportunities, it is reasonable to expect that they will lead to a more rapid growth of productivity in large sectors than in small ones. In short, our model puts forward the hypothesis that it is the interaction between market size and technological opportunities that sustains sectoral productivity growth, rather than just the size of the industry.

3.1.3 Additional hypotheses and control variables

Schumpeterian regimes. As pointed out at the beginning of this section, recent empirical research in evolutionary economics has identified a relationship between the properties of sectoral technological regimes and the characteristics of market structure, i.e. the Schumpeter Mark I and II regimes. Building upon this strand of applied research, our model puts forward the hypothesis that the relationship between technological regimes and sectoral productivity growth differs in the Schumpeter Mark I and II patterns.[12]

The idea is that the mechanism that links industry-specific characteristics to productivity gains may work differently in distinct sectoral market structures. In a Schumpeter Mark I, low cumulativeness and appropriability conditions tend to facilitate the continuous entry of new innovative firms. In this context, aggregate productivity growth in the industry is mainly the result of a process of creative destruction in a turbulent market, where new innovators are more productive than the exit firms they replace. In the Schumpeter Mark II regime, on the other hand, high cumulativeness and appropriability conditions create strong technological entry barriers for new innovators. Industry productivity growth in this type of market is therefore mostly the result of a continuous process of knowledge accumulation by well-established oligopolistic innovators, where the key sources of

[12] For a previous empirical work investigating a similar hypothesis, see Van Dijk (2000).

growth are thus represented by learning by doing, dynamic economies of scale and the persistence of innovative activities.[13]

In a nutshell, we thus assume that the relationship between technological regimes and sectoral productivity growth that our model explores will be different in the two Schumpeterian patterns. In econometric terms, this general hypothesis implies that (at least some of) the relationships between technological regimes, industry-specific characteristics and sectoral productivity growth that have been put forward in this section will have a different estimated coefficient in the Schumpeter Mark I and in the Schumpeter Mark II regimes.

Country-specific factors. One final point regards the existence of country specificities and their effects on the working of the model. Country-specific characteristics may play a relevant role to affect the growth of productivity of industrial sectors. In particular, the characteristics of *national systems of innovation* may create a set of opportunities and constraints for innovative activities of industrial sectors, and thus affect the economic performance of these (Nelson, 1993; Edquist, 1997; Mowery and Nelson, 1999). First, policies formulated at the national level have an important effect on various characteristics of sectoral regimes (e.g. appropriability regimes, education and skill levels). Secondly, other country-specific factors of a social, institutional and cultural nature may affect the interactions and cooperations among economic agents, thus affecting the extent to which external sources of opportunities are exploited by firms in sectoral systems of innovation (Malerba and Orsenigo, 1996). Thirdly, the specialization patterns and the macroeconomic performance of countries shape sectoral characteristics

[13] This idea is also consistent with a recent strand of applied microeconomic research that investigates the sources of productivity growth at the firm-level (for a recent critical discussion of this literature see Santarelli and Vivarelli, 2007, and for an extension to the service sectors see Lotti, 2007). Foster et al. (1998) review this body of research and present the results of a study that analyses the growth of productivity for a large number of manufacturing industries in the US by making use of plant-level data. Their decomposition exercise indicates that, within each manufacturing industry, productivity growth is greatly dependent on within-plant effects as well as on the process of reallocation via net entry, due to the fact that new entrants are more productive than the exit firms they replace. This and related analyses, by investigating the micro foundations of industry-level productivity growth, may indeed be relevant for achieving a deeper understanding of the microeconomic mechanisms underlying the dynamics of productivity in alternative Schumpeterian regimes.

such as technological opportunities, market size and the degree of openness to foreign competition.

Therefore, our model puts forward the hypothesis that the relationship between technological regimes and sectoral productivity growth may work somewhat differently in different national contexts. In econometric terms, this implies that country-specific factors must be controlled for in the empirical analysis of the links between technological regimes and sectoral growth.

4. Data and indicators

The empirical study makes use of industry-level data (2-digit level) for a sample of nine European countries (Germany, France, Italy, Netherlands, Norway, Portugal, Sweden, UK, and Austria) in the period 1996-2001. The data are from three different sources. Informations on the economic characteristics of each sector (e.g. labour productivity, exports) are taken from the OECD-STAN database. Data on education and skill levels of industrial sectors are obtained from Eurostat's Labour Force Survey (LFS). Indicators of innovative activities and sectoral technological regimes are calculated from the CIS-SIEPI database, a new dataset that contains data from the Second Community Innovation Survey (CIS2) on innovative activities in 22 manufacturing sectors in these nine European countries.[14]

CIS data have now become an increasingly important source of information for empirical analyses on innovative activities and performance of European firms, and they have frequently been used in the recent applied literature, particularly in the context of firm-level analyses for individual countries (e.g. Crepon et al., 1998; Evangelista, 1999; Mairesse and Mohnen, 2002; Cainelli et al., 2005; Reichstein and Salter, 2006). Some recent contributions, in particular, have made use of CIS or similar survey data for

[14] Compared to other CIS-related data sources (e.g. Eurostat), the CIS-SIEPI database contains industry-level data at a higher level of sectoral disaggregation (22 manufacturing industries, instead of 10 as in most other sources), and it therefore makes it possible to obtain a more accurate picture of sectoral innovative activities in Europe. The data are available at a higher level of sectoral disaggregation because they have been obtained directly from national sources (i.e. from the statistical offices of the countries included in the database) as a result of the EU-funded SIEPI project (2002-2004). The sectoral classification of the CIS-SIEPI database matches therefore the one of the OECD-STAN and the LFS, reason why it has been possible to combine these various data sources together.

constructing indicators of some of the main characteristics of sectoral technological regimes (Breschi et al., 2000; Marsili and Verspagen, 2002; Kaiser, 2002).
The attempt to measure technological regimes and other industry-specific characteristics by making use of survey data represents an important contribution to the applied literature in the field, given that previous empirical research had for the purpose made almost exclusively use of patent data. Based on these recent works, we extend this attempt and make use of CIS2 industry-level data in order to measure the characteristics of technological regimes of European manufacturing industries in the period 1994-1996.

Appropriability conditions (APPROPR): *percentage of innovative firms that have applied for at least one patent in the period*. This indicator is the only one available in the CIS-SIEPI dataset to measure the concept of appropriability. The variable refers mainly to patenting as the mean of appropriating the benefits of innovative activity, while it neglects other informal means, such as, for instance, process secrecy and know-how, and design and R&D know-how (Pavitt, 1984; Dosi et al., 2006). The indicator admittedly constitutes an imperfect measure of the concept of appropriability, but it nevertheless provides a useful indication on the propensity of innovative firms in each sector to protect their technological activities by using formal (rather than informal) means. A similar indicator of appropriability based on patent data has recently been used by Park and Lee (2006) in their analysis of technological regimes and catching up for the Korean and Taiwanese industries.

Cumulativeness conditions (CUMUL): *percentage of innovative firms that have been 'continuously' engaged in R&D activities in the period 1994-1996*. The indicator is used to measure the cumulativeness of the innovative process through the systematic and continuous R&D activities of innovative firms in each sector. It represents the concept of cumulativeness at the firm level proposed by Malerba and Orsenigo (1995, p. 59), according to which "firms continuously active in a certain technological domain accumulate knowledge and expertise".

Level of technological opportunities (OPPORT): *total innovation expenditures as a share of total turnover in the period 1994-1996*. Although "there is no consensus on how to make the concept of technological opportunity precise and empirically operational" (Cohen and Levin, 1989, p.1083), we believe this indicator to represent a satisfactory proxy for the level of technological opportunities in each sector. It is a widely used indicator of innovative input, and it provides a measure of the total effort done by firms to improve their technological activities.[15]

External sources of opportunities. CIS data contain a wide set of indicators to measure the ability of firms to take advantage of external sources of opportunities. In the CIS questionnaire, firms have been asked whether they cooperated with other firms in innovative projects in the period 1994-1996, and whether they regarded different actors in the system of innovation as a very important source of information for carrying out their technological activities. We use this set of questions in the survey to obtain a number of indicators of external sources of opportunities, and in particular of the intensity and direction of external linkages.[16]

Intensity of interactions (COOP): *percentage of innovative firms that have been cooperating in innovative projects in the period 1994-1996*. This is an overall measure of the *intensity* of interactions among innovators, and it provides a general indication of the extent to which firms try to exploit external sources of opportunities by collaborating with other actors in the innovation system (for a related indicator, see the empirical study of Malerba and Montobbio, 2003).

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[15] As compared to the R&D intensity, the indicator used in this paper is a broader measure of firms' *overall* innovative effort. In fact, firms tend often to rely upon a variety of innovative expenditures in addition to formal R&D activities, such as the acquisition of new machineries and equipments, training of personnel, preparation for production and delivery of new products, and design-related expenditures (Evangelista, 1999; Veugelers and Cassiman, 1999). This is the reason why we prefer to use an indicator of total innovative expenditures, rather than of R&D only.

[16] Kaiser (2002) has recently presented an interesting empirical study comparing the standard measures of knowledge spillovers commonly used in the R&D-productivity literature (see section 2 of this paper) with a set of CIS-based indicators of vertical linkages and external sources of opportunities, rather similar to those employed here. His empirical results suggest that CIS-based indicators perform in many cases better than the standard measures based on imported R&D expenditures, and thus provide encouraging support on the validity of the indicators that are presented here.

Direction of external linkages (USERS, COMPET, SCIENCE, PATDISCL, SUPPLIERS, CONSULT). These are indicators of the *direction* and type of external linkages, i.e. the actors that firms in different sectors tend to interact with (Pavitt, 1984).

USERS: *percentage of innovative firms that consider their 'clients' as a very important source of information for innovation*. The indicator is used to measure user-producer interactions (downstream linkages).

COMPET: *percentage of innovative firms that consider their 'competitors' as a very important source of information for innovation*. This variable gives an indication of the ability of firms to obtain knowledge and technical informations from their competitors in the same market, and it thus provides an idea of the available pool of intra-industry knowledge spillovers in each sector.

SCIENCE: *average of the percentage of innovative firms that consider 'Universities' and 'other public research institutes' as very important sources of information for innovation*. This is a measure of the interactions between innovative firms and the science system.

PATDISCL: *percentage of innovative firms that consider 'patent disclosures' as a very important source of information for innovation*. This represents a measure of the propensity and ability of firms to exploit advanced codified technical informations made available through patent disclosures.

SUPPLIERS: *percentage of innovative firms that consider their 'suppliers' as a very important source of information for innovation*. This is an indicator of supplier-producers interactions (upstream linkages).

CONSULT: *percentage of innovative firms that consider 'consultancy firms' as a very important source of information for innovation*. This variable provides an indication of the extent to which innovative enterprises make use of consultancy firms as providers of specialized knowledge and custom-specific technical and organizational solutions.

Human capital and skill levels (SKILLS, TRAIN). Data on education and skills at the industry-level are generally not available for large cross-country samples, and this has constituted a limitation to the use of this type of indicators in previous applied studies of innovation and sectoral productivity growth.[17] We make use of two indicators that are available for our industry-level sample of European economies, and that capture different (complementary) aspects of the links between human capital and growth.

SKILLS: *demand for high-skill labour as a share of the demand for medium-skill labour*. This indicator has been calculated from Eurostat's Labour Force Survey, where labour demand in each sector is broken down by the education level of the workforce (high, medium and low).[18] The indicator, by measuring the relative intensity of high vs. medium skills, provides a useful indication of the education level in each sector.

TRAIN: *percentage of innovative firms that have undertaken training expenditures directly linked to technological innovation in the period 1994-1996*. Differently from the previous, this variable is taken from the CIS-SIEPI database, where a question of the survey asked firms about their training activities. This indicator measures therefore a complementary aspect of the human capital formation, namely the effort undertaken by innovative firms to upgrade the technical competencies and skills of their employees.

Degree of openness (EXP): *share of the sector's exports on its valued added in 1996* (source: OECD-STAN database). The indicator represents a simple measure of the share of exports in each industry, which provides a basic indication of the openness of each sector to foreign competition.

Market size (MARKETSIZE): *share of the industry's turnover on the total turnover of manufacturing branches in the country* (source: CIS-SIEPI database). This variable measures the size of each sector in relation to the overall national production.

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[17] Two sources have previously been used in the empirical literature. One is data on skills disaggregated by industry collected by the OECD, which refer to a restricted sample of advanced countries in the early 1990s (Pianta, 2005; Piva et al., 2005). The other is the UNISD database of UNIDO, which contains the number of 'production' vs. 'non-production' workers as a share of total employment in each industry. The latter has frequently been used as an indicator of the skill level of the workforce, although it is admittedly a rather crude and imperfect measure of it (Machin and Van Reenen, 1998; Redding, 2002; Griffith et al., 2004).

[18] For the computation of the indicator, the labour demand for both high- and medium-skill are entered as mean values of the period for which data are available (1998-2001).

Productivity growth (PRODUCT): *average annual rate of growth of labour productivity between 1996 and 2001* (source: OECD-STAN database). For the computation of this indicator, the levels of labour productivity at the beginning and end of the period have been obtained by dividing the value added of each sector by its employment level; subsequently, the average annual growth rate of labour productivity for each industry between 1996 and 2001 has been calculated. This is the dependent variable of the econometric study that will be presented in the next section.[19]

5. Econometric results

The econometric model investigates the determinants of sectoral differences in labour productivity growth across 22 manufacturing industries in nine European countries in the period 1996-2001. The sample is cross-sectional, where most of the explanatory variables refer to the beginning of the estimation period, while the dependent variable (labour productivity growth) refers to the entire time span.

Table 1 presents some descriptive statistics of the indicators, and table 2 reports the coefficients of correlation between the explanatory variables in the regression model. The correlation matrix indicates three possible sources of multicollinearity in the regressions. First, the cumulativeness variable (CUMUL) is correlated with some of the other indicators of technological regimes, namely appropriability conditions (APPROPR), opportunity levels (OPPORT) and, more strongly, the intensity of interactions (COOP). This is not surprising, and may well be expected in the light of the results of recent empirical works on technological regimes and Schumpeterian patterns of innovation (e.g. Breschi et al., 2000). Secondly, regarding the external sources of opportunity, the intensity of interactions (COOP) is correlated with some of the variables measuring the direction of external linkages, such as USERS and SCIENCE. Thirdly, some of the coefficients of correlation among the indicators measuring the direction of external

[19] As discussed in section 2, in the mainstream R&D-productivity literature the standard way to measure productivity is to use an indirect measure, namely the total factor productivity (TFP). The empirical analysis undertaken in this paper is not based on a production function approach, and it consequently does not use the TFP-based empirical method that is closely related to that approach. For a discussion of different methods of productivity measurements and the underlying theoretical views, see Bartelsman and Doms (2000), Hulten (2000) and Heshmati (2003).

sources of opportunities are high (e.g. USERS with COMPET, SCIENCE with PATDISCL), suggesting that some of these variables may measure the same type of external linkages. These three possible sources of multicollinearity will be taken into account in the presentation and discussion of the regression results and, when appropriate, will be taken care of by omitting or transforming the corresponding variables.

< Tables 1 and 2 here >

The estimation makes use of the White ("sandwich") estimator, a commonly used method that takes into account possible problems of heteroschedasticity in the regressions. All estimations include, in addition to the set of explanatory variables, a set of country dummies that control for country-specific factors. These are found to significantly increase the explanatory power of the model, thus confirming that country-specific factors related to the characteristics of national systems of innovation play a relevant role for the explanation of sectoral differences in productivity growth.

Table 3 presents the results of the base regressions. The explanatory variables are entered gradually in the regressions reported in the various columns. In the first one, only the indicators of technological regimes are entered, whereas the other regressions additionally include the set of industry-specific characteristics pointed out in section 3 (which may therefore be considered as control variables whose inclusion can mediate or moderate the effects of technological regimes on productivity growth). In particular, in the second column, education and skill levels are included; in the third and fourth regressions, the export and market size variables are additionally entered; the fifth regression introduces a variable of interaction between opportunity levels and the intensity of external linkages.

Regarding the appropriability conditions, the estimated coefficient of the variable APPROPR turns out to be significantly negative in all the regressions in table 3, and it is quite stable when the set of industry-specific control variables are progressively introduced in the regressions. Thus, in the whole cross-section of European manufacturing industries in the period 1996-2001, the efficiency effect appears to have had a stronger consequence on productivity growth than the incentive effect. As pointed out in section 3, the efficiency effect is due to the fact that when appropriability conditions are lower, there is a greater scope for other firms in the same sector to imitate and to adopt the new technologies introduced by innovating firms. Thus, the model indicates that in sectors with lower degrees of appropriability (through patents) there exists a greater potential for intra-industry knowledge diffusion, with a beneficial effect on the growth of productivity. This is consistent with the results of the previous empirical studies of Cohen and Levinthal (1989 and 1990) and Klevorick et al. (1995).

The estimated coefficient of the variable CUMUL is positive, as expected, but it is significant only in the first regression. When other industry-specific characteristics are added to the technological regime variables (columns 2 to 5), the estimated coefficient is not statistically precise. As suggested by the correlation matrix above, this is possibly due to a problem of multicollinearity in the regressions, given that the variable measuring cumulativeness conditions is correlated with the other indicators of sectoral regimes, and it is therefore hard to estimate its relevance in the regression model with statistical precision. Thus, the hypothesis formulated in section 3 on the positive link between cumulativeness of innovative activities and sectoral productivity growth (Nelson and Winter, 1982, p. 351) finds moderate support, but cannot be confirmed with accuracy in the extended version of the model.

The level of technological opportunities turns out to be an important variable in the regression model, both as individual regressor and in interaction with other indicators. The estimated coefficient of the variable OPPORT has in fact the expected positive sign, and its magnitude progressively increases when additional variables are included in the regressions (see columns 1 to 4). Thus, sectors with a greater amount of total innovative expenditures, i.e. with higher levels of technological opportunities, have experienced higher rates of growth of labour productivity over time. This confirms the hypothesis of a positive relationship between the level of technological opportunities and the growth of productivity, which is based on a paradigmatic view of innovation and growth (Dosi, 1988, p. 1160) and consistent with the results of previous empirical works in this field (e.g. Nelson and Wolff, 1997).

The fourth variable we consider in the set of technological regimes indicators is COOP, which measures the intensity of interactions and cooperative agreements that firms undertake with other actors in the innovation system. The variable does not turn out to be significant in the regressions, and this is possibly determined, as suggested above, by a problem of multicollinearity with the variable CUMUL. In fact, additional regressions not reported here indicate that the variable COOP turns out to be positive and significant if we exclude CUMUL from the regressions.

Let us now turn to the set of other industry-specific characteristics considered in the model and the related interaction variables. The education and skill levels, the indicators employed to take into account complementary aspects of the human capital formation in each sector, have the expected positive sign and a stable coefficient in the various regressions: SKILLS, measuring the general education levels of the workforce, and TRAIN, focusing on specific technical skills that are continuously upgraded through training activities carried out within innovative firms. The result of a positive relationship between education and skill levels and sectoral productivity growth is of course in line with a large literature on technological change, human capital and growth. This result is important because, despite of the existence of a huge amount of applied studies at the macroeconomic level, this relationship has seldom been investigated at the sectoral level, due to the limited availability of industry-level data on human capital for a large sample of countries.

The more recent literature also suggests the possible existence of interactions and feedback relationships between human capital and technological change (see section 3.1.2). In order to take this aspect into account, we have also included variables of interaction between the level of technological opportunities and the indicators of education and training respectively. The first interaction variable (SKILLS·OPPORT) is not at all significant, and the corresponding regression has not been reported in table 3. The other interaction variable (TRAIN·OPPORT) is on the other hand significant in the regression in column 4, and its estimated coefficient turns out to be negative. The negative sign may at first sight appear puzzling, given that it would be reasonable to expect the interaction between the skill upgrading process and technological opportunities to be positively related to the growth of productivity in each sector. A possible interpretation of this finding, though, may be that in industries characterized by radical technological change (high opportunities) firms need to undertake significant efforts to rapidly upgrade the technical and organizational skills of their employees by means of training activities, and this required investment in human capital may possibly decrease the efficiency of the productive process and the productivity of labour in the short-run. In the longer-term, this argument would no longer be valid, and we would expect the joint presence of technological opportunities and training activities to result in productivity gains for the innovative firms.

Regarding the indicator of the degree of openeess of each sector, the variable EXP has a positive and significant estimated coefficient in the regressions reported in columns 3 to 5. The magnitude of the coefficient is large, and, in line with the model's expectations, it indicates the existence of a strong positive relationship between export and productivity growth across European manufacturing industries. Besides, we have also included a variable of interaction between exports and the level of technological opportunities, following the insights of technology-gap trade theory of a close link between technological change and trade performance. This interaction variable turns out to have a negative estimated coefficient (see columns 3 and 4). This suggests that new technological opportunities are transformed more rapidly into productivity gains when the sector is not exposed to foreign competition. The reason may be that in this case the industry has the time to adopt, implement and commercialise the new technologies in the home market first, before competing in the international arena. In other words, while export-oriented industries grow faster because of economies of specialization and efficiency gains induced by foreign competition on *already existing* goods, less exports-oriented sectors may have better chances to transform technological opportunities into *new* products and processes, and to commercialise them in the home market first. Again, this is an interpretation that may be reasonable when referred to a relatively short time span like the one considered in this paper, while in a much longer time frame we should expect the interaction between openness and technological change to be positively related to the dynamics of labour productivity in each sector.

Column 4 introduces two additional regressors, namely the size of each industry and the interaction of this with the level of technological opportunities. The estimated coefficient of the former (MARKETSIZE) turns out to have a significantly negative sign. Hence, the scale effect, i.e. the positive relationship between market size and productivity growth previously pointed out in the context of macroeconomic growth models (e.g. in post-keynesian economics and, more recently, in new growth theory), does not find support in our cross-industry model. On the contrary, it appears that the lower the sector's share in national manufacturing industries, the higher its rate of productivity growth. This may be due to the fact that dynamic and emerging sectors, that still account for a relatively small share of the overall manufacturing production, have grown rapidly in the period, while more traditional industries, which still constitute the bulk of manufacturing activities in Europe, have experienced a less dynamic performance.

On the other hand, the estimated coefficient relative to the interaction variable (MARKETSIZE·OPPORT) does not turn out to be significant at conventional levels. This interaction variable investigates the hypothesis that new technological opportunities may more rapidly be transformed into productivity gains when the sector is large. The reason may be that in large sectors there is greater scope for intra-industry knowledge diffusion, trial-and-errors, adaptation, incremental improvements and learning by doing mechanisms linked to the introduction and commercialisation of new technologies. In other words, the idea is that, to the extent that there are new technological opportunities, these lead to a more rapid growth of productivity in large sectors than in small ones. However, the regression results do not provide statistically accurate support for this hypothesis. This is an interesting aspect that should be further considered in future research, though.

The fifth column additionally includes a variable of interaction between the level of opportunities and the intensity of interactions (COOP·OPPORT). The hypothesis that was formulated in section 3 points out, in fact, that external linkages may be a more effective source of growth in sectors characterized by a dynamic technological environment, and that the interaction between external sources *and* levels of technological opportunities may therefore be an important factor to explain sectoral productivity growth. This interaction variable, however, does not turn out to significant in the estimations. Furthermore, its inclusion has a negative effect on the OPPORT variable, whose estimated coefficient decreases in magnitude and becomes not statistically significant.

The reason for this is the high correlation between the two variables (the coefficient of correlation between OPPORT and COOP·OPPORT is 0.88). Taking this into account, the additional exercises that will be reported in the remaining of this section will present separate regressions with and without this interaction variable, in order to check for the stability of the results to its inclusion.

< Table 3 here >

As previously pointed out, the variable COOP measures the *intensity* of interactions and cooperative agreements, which may be considered as a proxy for the overall effort of innovative firms to take advantage of external sources of opportunities. However, the regressions presented so far did not consider any of the indicators measuring the *direction* of these external linkages. The reason is that some of these variables are correlated with COOP and, in addition, some of them are closely related to each other (see correlation matrix above). This is likely to lead to a problem of multicollinearity in the regressions. In order to try to overcome this problem, we have run a factor analysis (principal component method) that studies the pattern of correlations among the indicators measuring the direction of external linkages. The results of the factor analysis are displayed in table 4. They show that three main principal components have been extracted, which jointly explain 80% of the variance in the cross-sectoral sample. The first factor measures *market interactions and downstream linkages*, given that it loads very high on the variables COMPET and USERS (interactions with the competitors in the same market and with the users respectively). The second principal component may be interpreted as an indicator of *science interactions and patent disclosures*, and it is highly correlated with the variables PATDISCL and SCIENCE. The third factor is a measure of *upstream linkages*, given that it loads high on the indicators of interactions with the suppliers (SUPPLIERS) and with consultancy firms (CONSULT), which are in fact suppliers of advanced knowledge and custom-specific solutions.

These results are useful because they suggest which indicators of the direction of external linkages it is more appropriate to include in the regression model in order to avoid the presence of multicollinearity among them. Table 5 presents the results of additional regressions that, in addition to the set of explanatory variables already presented in table 3, do also include some of these external sources variables. In particular, columns 1 and 2 introduce the three principal components extracted by the factor analysis, while columns 3 and 4 insert one indicator corresponding to each of them, namely USERS for factor 1, SCIENCE for factor 2 and SUPPLIERS for factor 3.

None of these variables turn out to be significant in the estimations, though. Furthermore, their inclusion leads to a loss of statistical precision of some of the other regressors. This is particularly the case in the regressions reported in columns 1 and 2, where the variables measuring appropriability, opportunity levels, training, degree of openness, market size, and the related interaction variables, become not statistically significant when the three principal components are included in the regression model. The results reported in columns 3 and 4, on the other hand, are quite similar to the base results (see the corresponding regressions in table 3, columns 4 and 5), the only difference being the loss of significance of the variables OPPORT and TRAIN.

On the whole, the results presented in table 5 do not provide precise indications on the role of this type of external linkages variables on the growth of sectoral productivity. One possible reason is that these indicators measure the *direction* of external linkages, which does greatly vary in different groups of industries. In particular, the innovation literature has shown that traditional and low-tech sectors frequently make use of suppliers-producers interactions, whereas other more advanced industries tend to interact with the users or with the science system (Pavitt, 1984). This means that each of these indicators is likely to have an effect on productivity growth in a restricted group of sectors but not in others, and this may explain why its overall estimated effect is not significant in the whole cross-industry sample.[20]

< Tables 4 and 5 here >

[20] An interesting exercise to explore further this hypothesis would be to make use of firm-level data and investigate the relationship between the direction of external linkages and the growth of productivity in different groups of industries. A firm-level sample would make it possible to investigate the hypothesis that upstream (downstream) linkages are more relevant for enterprises in supplier-dominated (specialised suppliers) sectors, whereas University-industry links represent a more important growth channel for firms in science-based industries.

The last hypothesis that was put forward in section 3 refers to the expected differences between the Schumpeter Mark I and the Schumpeter Mark II patterns in terms of the relationships between technological regimes, industry-specific characteristics and sectoral productivity growth (see section 3.1.3). Table 6 presents some main characteristics of the Schumpeterian regimes (EU average) and reports the results of two statistical tests of their differences, the ANOVA and the Mann-Whitney U test (the latter is a non-parametric test that, differently from the ANOVA, does not require the distributions to be normal and to have equal variances). The two tests lead to the same results, and indicate that the differences between Schumpeter Mark I and II are indeed substantial with respect to nearly all of the indicators used in our regression model (the only exception being the variable USERS, for which the differences across the regimes do not turn out to be significant at conventional levels).

In the Schumpeter Mark II structure, which is typically characterized by the presence of large oligopolistic innovators, industries have on average higher levels of cumulativeness, opportunities and appropriability (through patents), greater education and skill levels, a stronger intensity of interactions (particularly with the science system), a greater export propensity, a larger market size, and a more rapid growth of labour productivity.[21]

What do these differences imply in terms of the relationships between technological regimes and the dynamics of productivity – how does our model differ in these alternative Schumpeterian regimes? Table 7 investigates this question by presenting the results of regressions that include, in addition to the main explanatory variables (see table 3), a set of constant and slope dummies for the Schumpeter Mark II regime. These dummies in multiplicative form investigate the hypothesis that the slope and the intercept

[21] The distinction between Schumpeter Mark I and II regimes, while clear from a conceptual point of view, is not easy to apply in empirical analyses, given that there exist no well-established criteria to decide whether each manufacturing sector of the standard industrial classification belongs to one or the other regime. Previous empirical studies in the field, however, have carefully analysed this aspect and provided a list of industries belonging to each Schumpeterian regime. See, in particular, Malerba and Orsenigo (1995, p. 58; 1996), Breschi et al. (2000, p. 400) and Marsili and Verspagen (2002, pp. 814-815). Our division of manufacturing industries into Schumpeter Mark I and II regimes follows therefore these previous works, and it is reported here. *Schumpeter Mark II industries*: coke, refined petroleum products and nuclear fuel; chemicals; rubber and plastics; office and computing; radio and TV; motor vehicles. *Schumpeter Mark I sectors*: textiles; wearing; leather and footwear; wood and related; pulp and paper; printing and publishing; other non-metallic mineral products; basic metals; fabricated metal products; food and beverages; machinery and equipments; electrical; medical and optical; other transport equipment; furniture; recycling.

of the model differ between the two regimes (Gujarati, 1970). Although we started out with slope dummies for all the regressors, only the ones that contribute to the explanatory power (reduce the residual variance) of the model were retained in the final specification presented in table 7.[22]

The regressions in columns 1 and 2 introduce a constant dummy for the Schumpeter Mark II group of industries. These dummies are statistically significant, and their inclusion does not determine any important change in the estimated coefficients of the other variables (as can be observed by comparing these two columns in table 7 with the corresponding columns 4 and 5 in table 3). The other two regressions, in columns 3 and 4, include the set of slope dummies that have been found to be statistically significant, the introduction of which increases considerably the overall explanatory power of the model.

The first refers to the level of opportunities variable (SD OPPORT), whose estimated effect on sectoral productivity growth turns out to be much stronger (nearly the double) in the Schumpeter Mark II than in the Schumpeter Mark I regime, thus suggesting that large well-established producers are on average better able to rapidly transform new technological opportunities into productivity gains. The second important slope dummy is the one relative to the indicator of education levels (SD SKILLS). This suggests that the estimated relationship between human capital and growth is much stronger in the Schumpeter Mark II regime, an indication of the fact that large innovators are better able to attract more educated workers, with beneficial effects on their economic performance.

Further, the slope dummies for the training variable (SD TRAIN) and its interaction with the level of opportunities (SD TRAIN·OPPORT) do also turn out to improve the explanatory power of the model. Both slope dummies have the same signs as the corresponding variables, and the interpretation is therefore the same provided above with reference to table 3. Their estimated coefficients suggest that the positive effect of training activities on productivity growth, and the related negative effect of their interaction with technological opportunities, is much stronger (about the double) for large oligopolistic producers, given that these can devote a larger amount of resources to

[22] When a slope dummy is included in the final specification in table 7, the estimated coefficient for the Schumpeter Mark II regime is the algebraic sum of the overall estimated coefficient of the regressor and the one of the corresponding slope dummy. On the other hand, if the slope dummy is not included, the estimated coefficient is the same for the two regimes.

training activities specifically related to the introduction of new products and processes. Finally, the fifth slope dummy retained in the model is the one for the variable measuring the intensity of cooperative agreements (SD COOP), whose estimated coefficient turns out to be negative for the Schumpeter Mark II regime. A possible interpretation of this finding is that, in different types of market structure, firms adopt different strategies to take advantage of external sources of opportunities, and these strategies have distinct effects on their economic performance. In a Schumpeter Mark II context, in particular, industries with a greater propensity to collaborate with external partners seem to have experienced a less rapid growth of productivity than sectors with a lower intensity of interactions.[23]

Summing up, the results presented in table 7 provide clear evidence on the existence of important differences in the working of the model in the two Schumpeterian patterns. In the Schumpeter Mark I, productivity growth in each sector is mainly the result of a process of creative destruction in a turbulent market, where new innovators are more productive than the exit firms they replace. In the Schumpeter Mark II, on the other hand, productivity growth is mostly the result of a continuous process of knowledge accumulation by well-established oligopolistic innovators, which are, on average, better able to transform new technological opportunities into productivity gains, and to actively invest in the formation of human capital and organizational capabilities by attracting highly educated workers and by upgrading continuously their skills and competencies.

< Tables 6 and 7 here >

6. Conclusions

The paper has proposed to extend the R&D productivity literature in a novel direction. Instead of following the standard approach, which focuses on the role of R&D activities and spillovers for the growth of sectoral productivity, we have argued that the economic

[23] This is a finding that could be explored further by means of firm-level data, which would make it possible to investigate more thoroughly the relationships between the cooperative strategies of firms, the market structure of their industries and their economic performance.

performance of industrial sectors is the outcome of the interplay of a more complex set of factors. The model presented here has in particular focused on the characteristics of technological regimes and other sector-specific economic conditions, and the impact that these may have on the dynamics of labour productivity. The empirical model has been estimated on a cross-section of manufacturing industries in nine European countries for the period 1996-2001. The major results of the econometric exercise may be summarized as follows.

Sectoral differences in labour productivity growth in Europe are significantly related to cross-industry differences in terms of several techno-economic factors, among which the most relevant and statistically significant variables are those measuring the following five aspects: (1) appropriability conditions; (2) levels of technological opportunities; (3) human capital levels, referring to both general education of the workforce and more specific skills continuously upgraded through training activities carried out by innovative firms; (4) the degree of openness to foreign competition; (5) the size of the market. The first and the last factors are negatively related to the dynamics of sectoral productivity, while the other three are positively linked to it.

Furthermore, this empirical relationship emerges more clearly when differences in terms of sectoral market structure are controlled for. The results indicate that the relationship between sector-specific characteristics and productivity growth differs substantially among the distinct types of market structure pointed out in the Schumpeterian literature. In the Schumpeter Mark II regime, differently from the Mark I pattern, large oligopolistic innovators appear to be better able to transform new technological opportunities into productivity gains and to actively invest in the formation of human capital and organizational capabilities, and productivity growth is thus greatly enhanced by this cumulative process of knowledge accumulation.

While the empirical results pointed out in this paper do on the whole provide basic support for the proposed model, it is nevertheless important to interpret them with caution. We thus conclude by pointing to some main limitations of the paper and, relatedly, to the possible extensions that this line of research may in the future explore.

First, two of the hypotheses put forward by the model, on the role of cumulativeness conditions and external sources of opportunities, cannot be confirmed with accuracy. The coefficients for these variables, though providing some interesting indications, do not turn out to be estimated with statistical precision. However, there currently exists a growing theoretical and empirical literature pointing out the important role of both of these factors for the technological and economic performance of firms in innovation systems. It is therefore important that future applied research in this field will carefully examine again these aspects in a different context, e.g. by making use of firm-level data for individual countries and by refining the indicators that have been used in this paper and complementing them with micro-level variables.

A second limitation of the study is that it has focused on manufacturing industries only and it has neglected the service sectors (due to a lack of relevant data for services). The latter, though, are playing an increasingly important role in the modern knowledge-based economy, particularly in relation to their important function in providing advanced knowledge to manufacturing industries (e.g. ICT-related services, consultancy services). A future extension of this work could therefore be to refine the empirical analysis presented here by also including service industries, thus further enriching the analysis of the relationships between technological regimes and productivity growth in a wider set of different industrial settings.

Finally, a third limitation is that the model presented in this paper has mainly provided a static picture of the relationships between industry-specific characteristics and sectoral productivity growth, where the former have been found to affect the latter in the context of a cross-sectional analysis in a relatively short time span (the second half of the 1990s). In a much longer period (say, in a time frame of a few decades), the model would necessarily have to be more complex, in order to take into account the existence of a set of feedback mechanisms and of the dynamic co-evolution among the different variables considered here. In particular, it would be reasonable to expect that the dynamics of productivity and the economic performance of industrial sectors will affect, in turn, the characteristics of technological regimes and other industry-specific conditions (e.g. human capital, export performance, market size), thus contributing to the transformation of sectoral systems of innovation in the long run. In other words, the explanatory variables of our model would become, in a longer time frame, endogenous factors. Technological and economic dynamics co-evolve in the long run.

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Figure 1: An evolutionary model of technological regimes and sectoral productivity growth

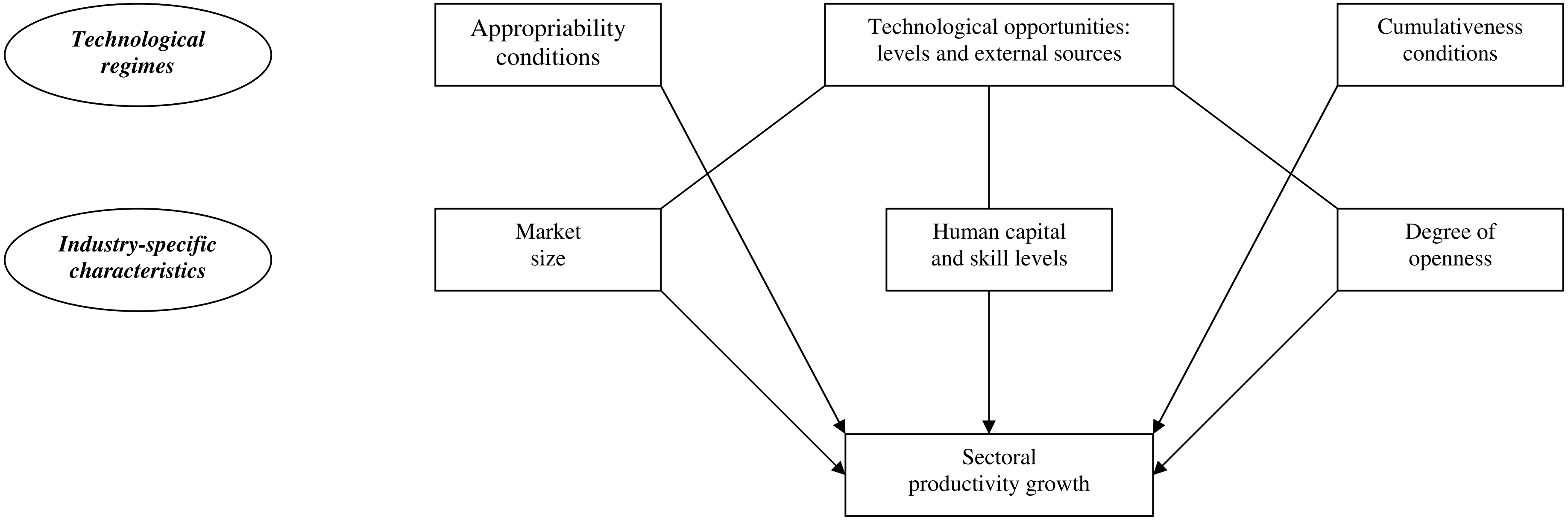

Table 1: Descriptive statistics.

	Median	Coefficient of variation	Minimum	Maximum
APPROPR	24.5	0.67	0.0	76.2
CUMUL	36.0	0.48	3.8	94.2
OPPORT	2.6	0.98	0.1	25.7
COOP	29.3	0.56	5.1	95.4
USERS	47.8	0.47	4.9	83.2
COMPET	14.1	0.56	1.3	43.7
SCIENCE	3.6	0.84	0.3	17.7
PATDISCL	1.9	0.97	0.1	17.1
SUPPLIERS	16.9	0.58	1.7	51.0
CONSULT	4.3	1.21	0.5	30.6
SKILLS	24.8	0.72	4.6	178.1
TRAIN	37.6	0.44	0.0	96.6
EXP	0.9	0.79	0.0	6.2
MARKETSIZE	3.2	0.91	0.3	31.9
PRODUCT	1.8	1.43	-6.9	38.3

Table 2: Correlation matrix: coefficients of correlation between the explanatory variables

	APPROPR	CUMUL	OPPORT	COOP	USERS	COMPET	SCIENCE	PATDISCL	SUPPLIERS	CONSULT	SKILLS	TRAIN	EXP	MARKETSIZE
APPROPR	1													
CUMUL	0.53	1												
OPPORT	0.35	0.41	1											
COOP	0.31	0.58	0.37	1										
USERS	0.28	0.28	0.17	0.52	1									
COMPET	0.26	0.11	-0.02	0.19	0.55	1								
SCIENCE	0.18	0.25	0.13	0.49	0.39	0.42	1							
PATDISCL	0.22	0.22	0.00	0.26	0.19	0.28	0.60	1						
SUPPLIERS	-0.34	-0.51	-0.13	-0.31	-0.18	-0.03	-0.10	-0.16	1					
CONSULT	-0.24	-0.42	-0.12	-0.28	-0.04	0.04	0.26	0.01	0.30	1				
SKILLS	0.03	0.32	0.30	0.26	0.01	-0.01	0.25	0.10	0.08	-0.12	1			
TRAIN	0.38	0.28	0.17	0.17	0.14	0.28	0.16	0.19	-0.27	-0.25	0.11	1		
EXP	0.08	0.23	0.00	-0.06	-0.17	-0.18	-0.02	-0.05	-0.16	-0.14	0.18	0.10	1	
MARKETSIZE	0.01	0.02	-0.10	0.09	-0.03	-0.01	0.03	0.11	-0.05	-0.03	0.03	0.09	-0.04	1

Table 3: Results of econometric estimation. *Base results*.
Dependent variable: average annual growth rate of labour productivity, 1996-2001.

	(1)	(2)	(3)	(4)	(5)
APPROPR	-0.089 (2.11)**	-0.074 (1.90)*	-0.075 (1.95)*	-0.077 (2.04)**	-0.067 (2.04)**
CUMUL	0.048 (1.90)*	0.025 (0.77)	0.001 (0.04)	-0.002 (0.07)	0.010 (0.30)
OPPORT	0.290 (1.71)*	0.660 (1.52)	0.963 (1.95)*	0.901 (1.96)*	-0.013 (0.02)
COOP	0.034 (0.83)	0.014 (0.31)	0.008 (0.20)	0.018 (0.45)	-0.041 (0.93)
COOP·OPPORT					0.013 (1.43)
SKILLS		0.083 (3.28)***	0.084 (3.70)***	0.082 (3.65)***	0.079 (3.64)***
TRAIN		0.057 (1.98)**	0.047 (1.68)*	0.058 (2.15)**	0.058 (2.23)**
TRAIN·OPPORT		-0.011 (1.31)	-0.010 (1.37)	-0.013 (1.70)*	-0.010 (1.28)
EXP			1.636 (2.18)**	1.634 (2.33)**	1.071 (1.94)*
EXP·OPPORT			-0.219 (1.65)*	-0.209 (1.78)*	-0.084 (1.01)
MARKETSIZE				-0.253 (2.11)**	-0.239 (2.14)**
MARKETSIZE·OPPORT				0.047 (1.42)	0.040 (1.32)
Country dummies	Yes	Yes	Yes	Yes	Yes
R^2	0.474	0.550	0.600	0.615	0.631
N	175	156	146	146	146

Heteroschedasticity-robust t values in parentheses.
*** Significance at 1% level; ** Significance at 5% level; * Significance at 10% level.

Table 4: Results of the factor analysis for the variables measuring *the direction of external linkages*: rotated component matrix and total variance explained

	Factor 1: MARKET	**Factor 2: SCIENCE**	**Factor 3: SUPPLIERS**
COMPET	0.905	0.181	0.071
USERS	0.920	0.117	-0.107
PATDISCL	0.047	0.890	-0.112
SCIENCE	0.316	0.826	0.140
SUPPLIERS	0.026	-0.203	0.824
CONSULT	-0.055	0.207	0.837
% of variance explained	29.53	26.73	23.81
Cumulative % of variance explained	29.53	56.26	80.07

Extraction method: Principal Component Analysis
Rotation method: Varimax with Kaiser Normalization

Table 5: Results of econometric estimation. *Adding the variables measuring the direction of external linkages*. Dependent variable: average annual growth rate of labour productivity, 1996-2001.

	(1)	**(2)**	**(3)**	**(4)**
APPROPR	-0.047 (1.06)	-0.043 (1.00)	-0.088 (2.06)**	-0.076 (2.03)**
CUMUL	0.016 (0.20)	0.018 (0.23)	-0.026 (0.57)	-0.014 (0.32)
OPPORT	0.688 (1.45)	0.350 (0.70)	0.713 (1.61)	-0.090 (0.16)
COOP	-0.066 (0.82)	-0.096 (1.01)	0.026 (0.43)	-0.032 (0.55)
COOP·OPPORT		0.009 (0.80)		0.012 (1.34)
SKILLS	0.075 (2.55)**	0.075 (2.57)**	0.085 (3.49)***	0.083 (3.50)***
TRAIN	0.035 (1.06)	0.034 (1.03)	0.029 (0.82)	0.037 (1.15)
TRAIN·OPPORT	-0.011 (1.43)	-0.011 (1.35)	-0.010 (1.28)	-0.007 (0.95)
EXP	1.257 (1.54)	1.287 (1.54)	1.694 (2.12)**	1.138 (1.69)*
EXP·OPPORT	-0.095 (0.98)	-0.102 (0.93)	-0.198 (1.75)*	-0.089 (1.03)
MARKETSIZE	-0.114 (1.10)	-0.109 (1.09)	-0.308 (2.00)**	-0.281 (2.04)**
MARKETSIZE·OPPORT	-0.006 (0.13)	-0.009 (0.20)	-0.053 (1.44)	0.046 (1.36)
F1 - MARKET	0.314 (0.45)	0.332 (0.47)		
F2 - SCIENCE	0.722 (1.08)	0.720 (1.07)		
F3 – SUPPLIERS	-0.207 (0.29)	-0.264 (0.38)		
USERS			0.013 (0.30)	0.023 (0.52)
SCIENCE			-0.063 (0.29)	-0.060 (0.29)
SUPPLIERS			-0.096 (1.57)	-0.083 (1.51)
Country dummies	Yes	Yes	Yes	Yes
R^2	0.605	0.608	0.634	0.647
N	111	111	138	138

Heteroschedasticity-robust t values in parentheses.
*** Significance at 1% level; ** Significance at 5% level; * Significance at 10% level.

Table 6: Main characteristics of the Schumpeter Mark I and II regimes: average values and statistical tests for their differences.

	Schumpeter Mark I	Schumpeter Mark II	ANOVA F	Mann-Whitney U test
APPROPR	24.3	34.4	18.13***	-4.22***
CUMUL	35.6	53.4	59.81***	-6.56***
OPPORT	3.6	5.7	14.69***	-3.87***
COOP	27.5	38.4	25.99***	-4.77***
USERS	40.5	45.1	1.41	-1.12
SCIENCE	3.4	5.4	19.38***	-4.46***
SUPPLIERS	19.7	14.7	7.34***	+2.58***
SKILLS	26.5	45.4	28.24***	-4.48***
TRAIN	37.6	42.7	3.24*	-1.83*
EXP	1.1	1.8	13.85***	-3.76***
MARKETSIZE	4.7	6.5	4.26**	-2.43**
PRODUCT	2.7	5.6	16.56***	-2.23***

*** Significance at 1% level; ** Significance at 5% level; * Significance at 10% level.

Table 7: Results of econometric estimation. *Adding constant dummy and slope dummies for the Schumpeter Mark II regime*.[a] Dependent variable: average annual growth rate of labour productivity, 1996-2001.

	(1)	(2)	(3)	(4)
APPROPR	-0.083 (2.17)**	-0.073 (2.19)**	-0.099 (2.56)**	-0.090 (2.64)***
CUMUL	-0.005 (0.16)	0.007 (0.25)	0.002 (0.07)	0.012 (0.38)
OPPORT	1.006 (2.13)**	0.064 (0.13)	1.240 (2.77)***	0.423 (0.84)
COOP	-0.004 (0.10)	-0.067 (1.44)	0.019 (0.49)	-0.035 (0.78)
COOP·OPPORT		0.013 (1.54)		0.012 (1.48)
SKILLS	0.073 (3.20)***	0.070 (3.13)***	-0.025 (0.94)	-0.022 (0.81)
TRAIN	0.062 (2.19)**	0.062 (2.31)**	0.073 (2.71)***	0.071 (2.68)***
TRAIN·OPPORT	-0.015 (1.72)*	-0.011 (1.37)	-0.019 (2.33)**	-0.016 (2.00)**
EXP	1.434 (2.07)*	0.842 (1.42)	1.642 (2.41)**	1.151 (1.89)*
EXP·OPPORT	-0.214 (1.87)*	-0.085 (1.10)	-0.257 (2.25)**	-0.146 (1.78)*
MARKETSIZE	-0.238 (1.97)*	-0.223 (1.97)*	-0.260 (2.24)**	-0.249 (2.30)**
MARKETSIZE·OPPORT	0.037 (1.18)	0.029 (1.01)	0.042 (1.43)	0.036 (1.33)
CD	1.957 (1.77)*	2.045 (1.82)*	-2.725 (1.76)*	-2.412 (1.48)
SD OPPORT			0.831 (3.83)***	0.821 (3.57)***
SD SKILLS			0.134 (4.12)***	0.131 (4.07)***
SD TRAIN			0.068 (2.53)**	0.072 (2.57)**
SD TRAIN·OPPORT			-0.017 (4.04)***	-0.018 (3.89)***
SD COOP			-0.047 (1.89)*	-0.047 (1.94)*
Country dummies	Yes	Yes	Yes	Yes
R^2	0.628	0.645	0.688	0.701
N	146	146	141	141

Heteroschedasticity-robust t values in parentheses.
*** Significance at 1% level; ** Significance at 5% level; * Significance at 10% level.
[a] CD and SD: Constant dummy and slope dummies for the Schumpeter Mark II regime.