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Fulvio Castellacci

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# **The interactions between national systems and sectoral patterns of innovation**

## **A cross-country analysis of Pavitt's taxonomy**

**Fulvio Castellacci**

Department of International Economics,  
Norwegian Institute of International Affairs (NUPI).  
Address for correspondence:  
NUPI, POB 8159, Dep. 0033 Oslo, Norway  
E-mail address: fc@nupi.no

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### **Abstract**

Do national and sectoral innovation systems interact with each other? The paper explores this unexplored question by carrying out a cross-sector cross-country analysis of European systems of innovation in the 1990s. The empirical study takes Pavitt's (1984) taxonomy as a starting point, and it investigates the cross-country variability of Pavitt's sectoral patterns of innovation. The analysis leads to three main results. First, the various technological trajectories show large differences across countries, due to the influence of national innovation systems. Second, there is evidence that the interaction between national systems and sectoral patterns of innovation constitutes an independent source of variability in the sample. Third, the analysis leads to the identification of eight sector- and country-specific technological trajectories in European manufacturing industries, and, based on that, proposes a refinement of Pavitt's taxonomy. The refined taxonomy, in a nutshell, suggests that sectoral systems must be supported by and interact with their respective national systems in order to become industrial leaders.

**Keywords:** National systems; Sectoral systems; Pavitt's taxonomy; Vertical linkages

**JEL Classification:** O30, O33, O57

## **1 Introduction**

The study of innovation systems has increasingly attracted the attention of academic scholars and policy makers in the last couple of decades. One strand of research in the innovation systems literature explicitly focuses on the national level, and investigates the characteristics and evolution of different national systems of innovation, and the impact of these on economic growth and competitiveness (Freeman, 1987; Porter, 1990; Lundvall, 1992; Nelson, 1993; Edquist, 1997 and 2005; Balzat and Hanusch, 2004). A related strand of research within the evolutionary field points out that, besides the existence of important country-specific factors, a relevant set of sector-specific circumstances greatly affect the patterns and performance of innovative activities. The investigation of these sectoral specificities constitutes, in a nutshell, the major purpose of the sectoral systems (or sectoral patterns) of innovation approach (Nelson and Winter, 1977 and 1982; Pavitt, 1984; Dosi, 1988; Malerba, 2005 and 2006).

These two strands of research have greatly enriched our understanding of both the country- and sector-specific nature of innovation. The two groups of studies are strictly related to each other, sharing an evolutionary interpretation of the process of economic change, and a systemic understanding of the nature of innovative activities (Castellacci, 2007a). The close relationship between these two strands of evolutionary research is evident, but, quite surprisingly, there does not exist any body of literature that systematically and explicitly investigates the mechanisms that link the meso and the macro level in innovation systems. Now, nearly two decades after the emergence of the innovation systems approach, it is important to raise one relevant question. Do national systems interact with sectoral patterns of innovation – and what are the main channels of interaction between the meso and the macro levels?

At a very general level, the idea that sectoral and national systems are intertwined has recently been proposed by Mowery and Nelson (1999), Murmann and Homburg (2001), Malerba (2005) and Balzat and Pyka (2006). The present paper develops this idea further, and explores the interactions between national systems and sectoral patterns of innovation. The paper argues that the characteristics and dynamics of sectoral technological trajectories are affected by a great variety of factors related to the national system of innovation, such as the patterns of technological, scientific and economic specialization, the country's economic performance and international

competitiveness, the characteristics defining the home market and other demand conditions, industrial and innovation policies, and other country-specific factors of a social, institutional and cultural nature. In turn, this wide set of characteristics related to the national system of innovation is affected and shaped over time by the properties of sector-specific trajectories.

This idea is quite general, and it provides a basic framework to interpret the findings of the empirical analysis undertaken in this paper. The work carries out a cross-sector cross-country statistical analysis of European systems of innovation, the main objective of which is to explore the interactions between national systems and sectoral patterns of innovation in European manufacturing industries. The empirical analysis is based on the CIS-SIEPI database, which contains CIS2 data on the innovative activity of 22 manufacturing sectors in ten European countries (Germany, Spain, France, Italy, Netherlands, Norway, Portugal, Sweden, UK, and Austria; see Appendix 1 for details on the dataset).

The work is organized as follows. Section 2 takes Pavitt's (1984) taxonomy as a starting point, and argues that the latter still constitutes a powerful conceptualization of the intersectoral linkages that tie together different types of manufacturing industries. The section estimates a multinomial logit model in order to test the empirical relevance of Pavitt's taxonomy to explain sectoral patterns of innovation in Europe in the 1990s, and finds that the taxonomy performs significantly better when country-specific factors are included in the model.

Section 3 runs a set of two-way ANOVA tests, which investigate the cross-country variability of the sectoral trajectories identified by Pavitt, as well as the relevance of a factor of interaction between national systems and sectoral patterns. The evidence presented in the section indicates that sectoral trajectories differ greatly across European countries, and that the factor of interaction between national systems and sectoral patterns represents an independent source of variability in the sample.

Motivated by these findings, section 4 carries out a classification and regression tree analysis (CART, see Appendix 2), which aims at identifying the different sector- and country-specific technological trajectories that characterize European manufacturing industries, and, based on that, it proposes a refinement of Pavitt's taxonomy. The refined taxonomy, in a nutshell, suggests that sectoral systems must be supported by and interact with their respective national systems in order to become industrial leaders (Mowery and Nelson, 1999).

Section 5 concludes the paper by briefly discussing some of its main limitations and by pointing out some possible future extensions of the work. The concluding discussion makes clear that the paper constitutes an attempt to shed new light on the (still unexplored) interactions between national systems and sectoral patterns of innovation, but that the complexity of this topic and the lack of previous studies investigating it make it difficult to obtain clear-cut and conclusive results. The overall contribution of the paper, therefore, is not to provide definitive answers, but rather to open up new questions and to point to a new direction of research in the innovation system literature.

## **2 A test of Pavitt's taxonomy**

In a seminal paper, Keith Pavitt (1984) pointed out the existence of some major technological trajectories in manufacturing industries, and proposed a taxonomy of sectoral patterns of innovation based on these industry-specific trajectories. His categorization has become an important pillar in evolutionary studies of industrial dynamics, and has inspired a great amount of work dedicated to exploring the sector-specific characteristics of the innovative process (Archibugi, 2001). Although some refinements of this taxonomy have recently been proposed (Tidd et al., 1997; Evangelista, 1999; Marsili and Verspagen, 2002; Castellacci, 2007b), Pavitt's original conceptualization still constitutes a fundamental starting point for investigating how innovation differs across sectors (Malerba, 2005).

Pavitt (1984) focused on some important industry-specific characteristics of innovative firms in Britain in the period 1945-1979, and identified four major sectoral patterns of innovation: science-based, specialized supplier, scale intensive, and supplier-dominated sectors. Firms in *science-based industries* are typically large, and make great use of internal sources (e.g. R&D labs) to produce innovations. The knowledge base is complex and heavily dependent on scientific advances, so that a major source of technological change is constituted by the interactions between private firms and the public science system (i.e. Universities and other research institutes). *Specialized suppliers* are predominantly constituted by small firms that are specialized in the production of advanced equipments and precision machineries (product innovations). These industries innovate mostly by making use of internal

sources (such as engineering and design capabilities), and by interacting with the advanced users of new technologies, i.e. firms in other sectors that purchase equipments and machineries produced by the specialized suppliers and use them in the productive process.

*Scale intensive* sectors are among these advanced users. They interact intensively with the specialized suppliers in the innovative process by acquiring from them precision instruments and other specialized machineries, and by integrating the related design capabilities in their own R&D and production engineering departments. The knowledge base is complex, and to some extent dependent on scientific advances, although much less than in science-based industries. Firms in these sectors are typically large, given that they try to exploit learning by doing mechanisms and scale economies linked to plant and market size, and they introduce both product and process innovations. Finally, *supplier-dominated* industries constitute the least technologically advanced part of the manufacturing branch. They generally do not develop their innovations internally (i.e. in R&D labs and in production engineering departments), but rather introduce cost-saving process innovations by acquiring and implementing advanced technologies, equipment and materials produced in other sectors. In short, their trajectory is characterized by embodied technological change undertaken by SMEs with relatively low innovative capabilities.

Pavitt's taxonomy constitutes a simple and at the same time powerful conceptualization of the intersectoral linkages existing between different parts of the manufacturing branch of the economy. Its analytical power does not simply reside in the identification of four different sectoral technological trajectories, but it also refers to the focus on the vertical (upstream and downstream) linkages that tie together these four major types of industries. Thus, the most original contribution of Pavitt's taxonomy is arguably its focus on the intense intersectoral exchange of advanced knowledge, both in disembodied and in embodied form, that continuously arises in the innovative process.

From an empirical point of view, Pavitt's taxonomy was based on the analysis of a SPRU dataset containing information on various characteristics of innovative firms in Britain in the period 1945-1979. This leads to the question: how does the taxonomy perform when we focus on a more recent period, and consider a broader set of European countries? In order to answer this question, we now present the results of a test of Pavitt's taxonomy.

The test is carried out on the CIS-SIEPI database (see Appendix 1 for details). This dataset contains data from the Second Community Innovation Survey on innovative activities in 22 manufacturing sectors in ten European countries (Germany, Spain, France, Italy, Netherlands, Norway, Portugal, Sweden, UK, and Austria).<sup>1</sup> Six indicators have been constructed to measure the factors that Pavitt originally used to construct his taxonomy.<sup>2</sup>

(i) **INTERNAL**: *R&D and design expenditures as a percentage of total innovation costs*. This is an indicator of the internal sources of technology creation.

(ii) **SCIENCE**: *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 science-based sources of innovation.

(iii) **PROCvsPROD**:  $[(\text{Number of process innovators} - \text{number of new product innovators}) / (\text{Number of process innovators} + \text{number of new product innovators})]$ . This indicator distinguishes between those sectors predominantly oriented towards the introduction of new processes (PROCvsPROD closer to +1), and those mainly engaged in the creation of novel products (PROCvsPROD closer to -1). The variable is therefore used as an indicator of the relative importance of process and product innovations, and hence of the relative importance of innovations ‘used’ vs. innovations ‘produced’ in each industry.

(iv) **SIZE**: This variable is defined by the formula:  $[(\text{Total innovative expenditures by large firms} - \text{total innovative expenditures by SMEs}) / (\text{Total innovative expenditures by large firms} + \text{total innovative expenditures by SMEs})]$ . The index ranges between +1 (indicating a stronger relevance of large innovators) and -1 (where the role of SMEs is more important), and it is therefore used as a measure of the relative size of innovators in each sector.

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<sup>1</sup> Due to some missing values for some of the variables for Germany and Spain, the results of the test presented in this section do not include these countries, and therefore refer to a sample of eight countries.

<sup>2</sup> These are the so-called Pavitt’s “measured characteristics” (see tables 1 to 3 of his 1984 article).

(v) **USERS:** *Percentage of innovative firms that consider their clients as a very important source of information for innovation.* It is used as a proxy for the intensity of downstream linkages and user-producer interactions (Lundvall, 1992).

(vi) **SUPPLIERS:** *Percentage of innovative firms that consider their suppliers as a very important source of information for innovation.* It is used as a measure of the intensity of upstream linkages between innovative firms and their suppliers.

These six indicators are the explanatory variables in our test. The test is constructed as follows. The dependent variable is the categorical (unordered) variable “Pavitt’s taxonomy”, which takes value 1 for specialized suppliers sectors, 2 for science-based industries, 3 for scale intensive sectors, and 4 for supplier-dominated industries.<sup>3</sup> The purpose is to estimate the relationship between the choice of assigning sector  $i$  to group  $j$  (where  $j = 1, 2, 3,$  or  $4$ ) and the set of explanatory variables presented above. An OLS approach cannot be used in this case, because the explanatory variables are measured on a continuous scale, while the dependent is a categorical variable that takes only four values. The standard way to solve this problem is to estimate a multinomial logit (MNL) model (Scott Long, 1997; Peracchi, 2001). This is commonly expressed as:

$$\Pr \{ Y_i=j \} = \exp(\beta_j^T X_i) / 1 + \sum_k \exp(\beta_k^T X_i) \quad \text{for } j = 2, 3, \dots, J \quad (1)$$

$$\Pr \{ Y_i=1 \} = 1 / 1 + \sum_k \exp(\beta_k^T X_i) \quad \text{for } j = 1 \quad (2)$$

where  $X_i$  is a vector of characteristics specific to sector  $i$ , and  $\beta_j$  is a vector of coefficients specific to group  $j$ .<sup>4</sup> The multinomial logit model is essentially a “linked set of binary logits” (Scott Long, 1997). In our case, the model simultaneously estimates three binary logits, i.e. a vector of coefficients  $\beta_j$  for the specialized suppliers, science-based and scale intensive groups relative to the supplier-dominated

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<sup>3</sup> For a complete list of sectors included in each category of the taxonomy, see Appendix 1.

<sup>4</sup> Equations (1) and (2) are nonlinear, and require an iterative solution. This is based on the method of maximum likelihood. The solution is commonly found by the Newton’s method in a relatively small number of iterations.



category, which has been used as the reference category (for this reason, the latter is not reported in a separate column as are the other three groups).<sup>5</sup>

The results are reported in tables 1 and 2. Table 1 presents the results of the MNL test that does not take into account country-specific characteristics (i.e. the model without country dummies). The estimated coefficients for the model to a large extent confirm the characteristics of the four categories of Pavitt's taxonomy.<sup>6</sup> The coefficients relative to the variables measuring internal sources of technology creation and the process vs. product orientation are found to be significant for specialized suppliers and science-based industries, namely those groups that predominantly develop new products by using their own R&D labs and engineering and design capabilities. Science-based sources of innovation and a large firm size are both confirmed to be relevant factors for the science-based group and, to a lesser extent, also for the scale intensive category. These are in fact the industry groups where innovative firms are typically large and operate in a technological environment characterized by a knowledge base that is complex and strongly dependent on scientific advances. Finally, the indicator measuring user-producer interactions is relevant for specialized suppliers, while the variable measuring the upstream linkages with the suppliers turns out to be a significant factor to distinguish between supplier-dominated sectors (the base category in the estimation) and the other groups.

On the whole, the results of the MNL test presented in table 1 provide basic support for the validity of Pavitt's taxonomy in our cross-industry cross-country sample. However, the overall explanatory (classificatory) power of the model, measured by the pseudo R-squared indexes and by the classification table, is not so high, particularly with reference to the specialized suppliers and scale intensive categories (see lower part of table 1).

The next model, presented in table 2, adds a set of country dummies to Pavitt's basic explanatory variables, in order to take into account the existence of country-specific factors that were not originally considered by Pavitt's taxonomy. The inclusion of the

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<sup>5</sup> The choice of the baseline category does not affect the results of the MNL test, so that any other category could have been chosen instead.

<sup>6</sup> In a MNL model, each estimated coefficient measures the proportional change in the 'log of the odds-ratio' of the dependent variable when the  $k^{\text{th}}$  regressor changes by one unit. In other words, if the estimated coefficient  $\beta_k$  is positive (negative), the likelihood of that response category will increase (decrease) by a factor of  $\beta_k$  for any unit change of the  $k^{\text{th}}$  regressor.

country dummies significantly improves the classificatory power of the MNL model. In fact, the pseudo R-squared increases by around 20%, and the percentage of cases correctly classified becomes higher for the specialized suppliers, scale intensive and supplier-dominated categories. The country dummies that turn out to be most significant and with high estimated coefficients are those relative to France and the Netherlands, particularly for the group of specialized supplier industries. In this sectoral group, the high negative estimated coefficients for these country dummies indicate that the probability that a sector is assigned to the specialized supplier (rather than the supplier-dominated baseline) category decreases if the industry belongs to France or the Netherlands, thus suggesting the relative weak position of these countries in the specialized supplier bunch of sectors.<sup>7</sup> The classificatory precision of the model for this sectoral group, as a consequence, notably increases from 40% to 73,3%.

Turning to the set of basic explanatory variables, their estimated coefficients in the model with country dummies still provide basic support to the characteristics of the taxonomy, although some of them differ slightly from the previous model. The most notable difference refers to the variables SCIENCE and USERS, which both turn out to be not significant in the estimations. A possible explanation of this finding is that the interactions between innovative firms, the science system and the users do not only vary across sectors, but are also characterized by a strong cross-country variability that is related to the characteristics and specificities of national systems of innovation (Nelson, 1993; Malerba and Orsenigo, 1995, p.49). When we control for these relevant country-specific factors, therefore, the estimates of the cross-sectoral dimension become less statistically significant. This finding will be further investigated in the following sections.

Summing up, the cross-sector cross-country tests reported in tables 1 and 2 provide basic support for the validity of Pavitt's taxonomy, but at the same time indicate that the latter performs better when country-specific factors are taken into account. This suggests that the cross-country dimension is a relevant factor to shed new light on sectoral patterns of innovation, and that Pavitt's taxonomy could therefore be refined by focusing on some major country-specific factors that interact with sectoral technological trajectories. The key to obtain such a refinement is the analysis of the

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<sup>7</sup> The relative position of different European countries in the various categories of Pavitt's taxonomy will be analyzed in further detail in section 4.

interactions between national systems and sectoral patterns of innovation, to which we now turn.

< Tables 1 and 2 here >

### **3 The cross-country variability of sectoral patterns of innovation**

Do national systems of innovation interact with sectoral technological trajectories, and why? More specifically, which are the major country-specific factors that shape, and are affected by, sectoral patterns of innovation? This section considers these questions by analyzing the cross-country variability of the categories of Pavitt's taxonomy.

Table 3 presents the results of an analysis of variance for the factors used by Pavitt to construct his taxonomy. More precisely, the table reports the results of a 2-way ANOVA test for each of Pavitt's *measured characteristics* (see previous section for the definition of these). The ANOVA tests investigate the different sources of variability of Pavitt's variables by exploring their relationships with three factors: (i) the factor *Pavitt*, which is a categorical variable representing the taxonomy's group to which each sector belongs; (ii) the factor *country*, a categorical variable that defines the country to which each sector belongs; (iii) *the interaction term* between the previous two factors.<sup>8</sup>

In other words, the purpose of each 2-way ANOVA test is to analyze and to compare the three different sources of variability of each Pavitt variable, namely the variability among sectoral patterns of innovation, the variability across national systems, and the variability arising from interactions between national systems and sectoral patterns of innovation. For each ANOVA test, table 3 reports the F-ratio for the significance of each factor, and the Partial Eta Squared, which is an index measuring the percentage of variability accounted for by each of the three factors.

First, the results show that the factor *Pavitt* is significant for all the variables, thus confirming the results of the previous section on the important differences existing

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<sup>8</sup> A related exercise has recently been presented by Evangelista and Mastrostefano (2006). Their paper analyzes the extent of country-, sector- and firm-specific sources of variability in a cross-section of manufacturing industries in Europe. However, their exercise differs from the one presented here in two main respects. First, the present paper focuses on the cross-country variability in relation to Pavitt's sectoral groups. Second, our analysis of variance does not only focus on the country- and sector-specific components, but it does also consider an interaction term between these factors.

between the four sectoral patterns of innovation originally identified by Pavitt. Second, the factor *country* is also significant for all the variables, suggesting the existence of large cross-country differences across European manufacturing sectors, due to the specificities of national systems of innovation. Looking at the Partial Eta Squared indexes, we observe that the cross-country variability is greater than the cross-industry one for the variable measuring the process vs. product orientation and, more evidently, for all the variables measuring systemic interactions and vertical linkages (i.e. SCIENCE, USERS and SUPPLIERS). Thus, for these variables, the variability related to national systems appear to dominate the one linked to sectoral patterns. This result is consistent with the NIS literature, according to which intersectoral linkages are greatly affected by country-specific characteristics such as regulations, policies, entrepreneurial cultures, and other social, institutional and cultural factors (Lundvall, 1992; Nelson, 1993; Malerba and Orsenigo, 1995, p.49). Third, the *interaction term* turns out to be significant only for the variables measuring the systemic interactions and vertical linkages that connect innovative firms with other actors in the sectoral system, that is the users, the suppliers, and the public science system. For these three variables, in fact, the Partial Eta Squared indexes indicate that the interaction term is stronger than the factor Pavitt, and it thus suggests that the interaction between national systems and sectoral patterns of innovation constitutes an independent source of variability in the sample, which accounts for between 27 and 44% of the total variability. From a statistical point of view, the significance of the interaction term in the 2-way ANOVA test may be interpreted by stating that the cross-sectoral variability among Pavitt's technological trajectories is affected by the characteristics of national systems of innovation and that, conversely, the latter are affected by sectoral patterns of innovation.

< **Table 3 here** >

This can also be seen by looking at the boxplots in figure 1, which give an idea of the extent of the cross-country variability for the various sectoral groups of Pavitt's taxonomy. Figure 1 reports three boxplot graphs, each focusing on one of the variables measuring systemic interactions and vertical linkages, i.e. SCIENCE, USERS and SUPPLIERS (in figures 1a, 1b and 1c respectively). In these graphs, the vertical bars represent the cross-country variability of the categories of Pavitt's

taxonomy, so that, for any given variable and sectoral group, the longer the bar the larger the variability across countries.

Figure 1a focuses on the factor SCIENCE. As expected, the science-based sectoral category has a higher median value than the other sectoral groups. The graph indicates, though, that the cross-country variability of this indicator for the group of science-based industries is larger than for the other industry groups. Figure 1b considers the variable USERS, and shows that the group of specialized suppliers, the one with the highest median value (as Pavitt's theory would in fact suggest), is characterized by large differences across countries. Finally, figure 1c focuses on the factor SUPPLIERS, the highest median value of which is, as expected, in the group of supplier-dominated industries. This boxplot suggests that the cross-country variability of the variable SUPPLIERS is indeed larger for supplier-dominated industries than for the other sectoral categories.

The interesting pattern emerging from these boxplots, then, is that the variable that best characterizes and describes the direction of vertical linkages of each industry group according to Pavitt's theory (i.e. USERS for specialized suppliers, SCIENCE for science-based, and SUPPLIERS for scale intensive and supplier-dominated sectors) is, in most cases, the one that presents the greatest cross-country variability. This supports the idea that sectoral patterns shape, and are in turn shaped by, country-specific national systems of innovation, and that, consequently, each category of Pavitt's taxonomy may be refined by taking into account its large cross-country variability.

**< Figures 1a, 1b and 1c here >**

The discussion has so far focused on the empirical evidence and the related statistical interpretation. Let us now turn attention to the theoretical interpretation of these findings. What are the channels through which sectoral patterns interact with national systems of innovation, and what is the role of vertical (upstream and downstream) linkages in this respect? At a very general level, the idea that sectoral and national systems are intertwined has previously been suggested by Mowery and Nelson (1999), Murmann and Homburg (2001), Malerba (2005) and Balzat and Pyka (2006). However, to the best of our knowledge, there does not exist any specific and detailed

theoretical account of the various mechanisms of interactions between the meso and the national level in the innovation systems literature.<sup>9</sup> In an attempt to explore this complex issue, we discuss some of these possible channels as follows.

A first channel of interaction refers to the performance of national systems. Various studies have previously shown that the intensity of upstream and downstream linkages between sectors affects the performance of a country, and contribute to determining (i) its technological specialization patterns (Malerba and Montobbio, 2003), (ii) its foreign competitiveness and trade performance (Andersen, 1992; Fagerberg, 1995; Laursen and Meliciani, 2000 and 2002), and (iii) its rapidity of structural change and productivity growth (Castellacci, 2007c). In turn, the country-specific patterns of scientific, technological and economic specialization affect, strengthen and reproduce over time the intersectoral linkages between producers, suppliers, users and the science system (Porter, 1990; Lundvall, 1992).

Second, the policy level constitutes a major channel of interaction between the meso and the macro level. In fact, the existence of important industries or core industrial areas where the country is specialized, with the related set of well-established vertical linkages that they entail, may shape regulations and governmental decisions at the national level, and affect in particular (i) innovation policies, (ii) industrial policies, (iii) IPRs regulations, and (iv) university-industry links (Mowery and Nelson, 1999). If national policies actively promote core industrial areas for a prolonged period of time, and neglect others, this policy strategy will affect the entire national system of innovation, which may eventually turn out to be locked into a specific path.<sup>10</sup> Conversely, national policies may directly affect cooperation patterns, intersectoral linkages and university-industry collaborations through a wide variety of incentives, schemes and regulations (Lundvall and Borrás, 2005; Mowery and Sampat, 2005).

Third, user-producer interactions and upstream linkages between suppliers and innovative firms are two major factors characterizing the home market. The latter, together with the related demand and other macroeconomic conditions, in turn, affect the intensity of intersectoral linkages (Porter, 1990; Lundvall, 1992; Mowery and

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<sup>9</sup> A recent paper by Dopfer et al. (2004) discusses the interactions between the micro, meso and macro levels of analysis in evolutionary economics. The theoretical discussion presented there constitutes an interesting and general framework to link the various levels of analysis in evolutionary theorizing. Differently from the use made in their paper, however, in the present work the term *meso* refers to the *sectoral* level of analysis, i.e. the study of the patterns and evolution of different industries.

<sup>10</sup> A specific example of this in relation to the Norwegian case is discussed by Narula (2002).

Nelson, 1999). Fourthly, a broad range of other country-specific factors, of a social, institutional, and cultural nature, affect, as well as are shaped by, the degree of trust and cooperation in the system and, relatedly, the intensity of intersectoral linkages and the exchange of advanced knowledge. Network interactions and systemic relationships are in fact embedded in, and co-evolve with, a complex set of social and cultural factors that are specific to a given national framework (Powell and Grodal, 2005).

In a nutshell, the theoretical interpretation proposed here is that the interaction between sectoral patterns and national systems of innovation may tend to strengthen and reproduce a given country- and industry-specific technological trajectory over time. The specific role of systemic interactions and vertical linkages, and of their persistent, enduring and context-dependent nature, is fundamental for explaining the cumulative and path-dependent dynamics that innovation systems follow over time.

The idea of the interaction (co-evolution) between national systems and sectoral patterns of innovation is consistent with various empirical studies that have previously shown the continuity and persistence of country- and sector-specific technological trajectories and specialization patterns over long periods of time (Archibugi and Pianta, 1994; Begg et al., 1999; Laursen, 2000; Cefis and Orsenigo, 2001; Fai and Von Tunzelmann, 2001; Laursen and Salter, 2005). Overall, the theoretical discussion carried out here provides a broad and general framework to interpret the empirical findings presented in this section, as well as those that will be presented in the next one.

#### **4 A refinement of Pavitt's taxonomy**

This section proposes a refinement of Pavitt's taxonomy that takes into account the cross-country variability of systemic interactions between innovative firms and other actors in the sectoral system (i.e. the users, the suppliers and the science system). The rationale for proposing this refinement has been discussed in the previous sections, where we have found that (i) Pavitt's taxonomy performs better when country-specific factors are taken into account, that (ii) there exists a strong cross-country variability of some of Pavitt's factors, and that, in particular, (iii) there exists a significant interaction between the sectoral and the national level with respect to the intensity of vertical (upstream and downstream) linkages. The following analysis will

therefore concentrate on the latter set of factors (i.e. the variables USERS, SUPPLIERS and SCIENCE) and neglect the other variables originally considered by Pavitt (1984).

The refinement of the taxonomy is obtained by carrying out a cluster analysis of manufacturing industries in Europe.<sup>11</sup> The clustering method employed is the classification and regression tree algorithm (CART, see Breiman et al., 1984), which is presented in further detail in Appendix 2. The main idea of CART is to perform a hierarchical set of successive binary splits of the sample, and to represent them visually through a classification tree diagram. At each step of the algorithm, a binary split divides the cases (industries) into two subgroups, by using the variable that makes it possible to obtain the best split. The best split, in this context, is the one that best separates an industry group from the others (see Appendix 2). Then, each subgroup (node) is subsequently split into two further subgroups, and so on. The advantages of the CART method are that (i) it makes it possible to find out *endogenously* both the input variable that best discriminates among the cases at each step, and the number of branches that the tree contains, and that (ii) the resulting structure of the data can be visualized and easily interpreted through the classification tree diagram, so that it is frequently possible to identify patterns that would otherwise be difficult to find.

Figure 2 reports the classification tree diagram that represents the sequence of splitting and the resulting (terminal and non-terminal) nodes, and table 4 specifies the characteristics of each terminal node. Figure 2 shows that the entire sample (root node) is initially split into two nodes, based on the industries' score on the variable SUPPLIERS. Node 2 identifies, in fact, a first group of supplier-dominated sectors. The following split is performed by using the variable SCIENCE, and it singles out a number of science-based industries in node 4. The next split separates a cluster of scale intensive sectors based on the variable SUPPLIERS (node 6). Subsequently, the non-terminal nodes 7 and 8 are split, and identify two different groups of specialized suppliers sectors (based on their scores on the variable USERS, in nodes 10 and 12), as well as a second cluster of science-based industries (node 11). Finally, the last step

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<sup>11</sup> In this cluster analysis, manufacturing sectors have been grouped according to the four categories of Pavitt's taxonomy, so that the results presented in this section refer to a sample of 40 observations (i.e. four industry groups in ten European countries).



identifies nodes 13 and 14, which comprise a second group of supplier-dominated and a second group of scale-intensive sectors.

< **Figure 2 here** >

Table 4 reports the characteristics of the eight industry groups (terminal nodes) that have been endogenously identified, and it shows for each the precise splitting conditions that the CART algorithm has used to single out the node, the countries included in the industry group, and the most characteristic feature of the industry group in terms of the intensity of systemic interactions and vertical linkages between innovative firms, the users, the suppliers or the science system.

The results of the classification tree analysis show the existence of an interesting pattern, where each of the original categories of Pavitt's taxonomy is clearly divided into two separate groups. This empirical finding constitutes the basis for proposing a refinement of Pavitt's taxonomy, which takes into account the interactions between national systems and sectoral patterns of innovation. The resulting *eight country- and sector-specific technological trajectories* are described as follows.

**1A. Specialized supplier industries in NIS with *strong* downstream linkages:**

This group comprises specialized supplier sectors in Germany, Austria, UK, Sweden, Norway and Spain, which are characterized by very intense interactions between innovative firms and the advanced users of new technologies (USERS = 63,6%). These strong linkages may be explained as the result of the technological specialization patterns of these countries, where specialized supplier sectors (e.g. mechanical engineering in Germany and Sweden) play a relevant role and develop in close interaction with the advanced users (i.e. the domestic scale intensive industries). In addition, national policies and other socio-institutional factors have also determined a highly systemic and very cooperative environment where intersectoral exchanges of advanced knowledge are encouraged.

**1B. Specialized supplier industries in NIS with *weak* downstream linkages:**

Differently from the previous group, specialized supplier sectors in France, the Netherlands, Italy and Portugal do not appear to be supported by the characteristics of the national system of innovation and, consequently, user-producer interactions are

rather weak (USERS = 32,2%, nearly the half than in the previous group). These countries are, in fact, predominantly specialized in traditional and low-tech industries (particularly Italy and Portugal) or agriculture and knowledge intensive services (the Netherlands, see Verspagen, 2005), so that the development of downstream linkages does not tend to be supported by the prevailing industrial structure. National policies, demand conditions and other socio-institutional factors may have also affected the degree of trust and cooperation in the system and hampered the development of user-producer interactions.

#### **2A. Science-based industries in NIS with *strong* university-industry links:**

This group includes science-based sectors in Germany, Austria, Norway and Sweden, countries where the most characterizing feature of this sectoral trajectory, the interaction between innovative firms and the public science system, is sustained and strengthened by the specific features of the national systems of innovation. The latter, in fact, promote university-industry links, particularly in some core areas of traditional strength (e.g. chemicals in Germany), and create an overall cooperative environment where exchanges of advanced knowledge between the private and the public sectors are favored (Mowery and Nelson, 1999; Mowery and Sampat, 2005; Laursen and Salter, 2005). Consequently, a very high percentage of innovative firms in this cluster (9,2%) consider the public science system as a very important source of information for producing new technologies.

#### **2B. Science-based industries in NIS with *weak* university-industry links:**

Science-based sectors in France, UK, the Netherlands, Italy, Spain and Portugal are characterized by much weaker University-industry links (SCIENCE = 4,2%, less than the half of the industries in the previous group). Again, this is partly the result of scientific and technological specialization patterns, and partly the consequence of policy strategies, socio-institutional factors and other characteristics of the national systems that have hampered the exchange of advanced knowledge between the public and the private spheres in these countries. This pattern, with special reference to the French, British and Italian innovation systems, is in line with the results of the various country studies contained in Nelson (1993, p.511).

### **3A. Scale intensive industries in NIS with *strong* upstream linkages:**

This group comprises scale intensive sectors in a great number of European countries (Germany, Sweden, Norway, UK, France, Italy and Portugal). In these national systems, scale intensive industries have represented core areas of development during the age of Fordism and mass production, and have thus sustained the post-War process of industrialization and catching up (e.g. the car industry in Germany, France and Italy; the metal sector in Norway; the shipbuilding industry in Sweden). These sectoral specialization patterns, in close interaction with the related industrial and innovation policies and other country-specific factors, have supported and reproduced over time the intense upstream linkages between innovative firms and their suppliers (i.e. the specialized suppliers of precision instruments and advanced equipment). Consequently, the variable SUPPLIERS in this group shows a much larger value (20,7%) than in the next one.

### **3B. Scale intensive industries in NIS with *weak* upstream linkages:**

In this group of sectors, in Austria, the Netherlands and Spain, upstream linkages are in fact significantly weaker (SUPPLIER = 8,2%). In these countries, the role of domestic scale intensive industries as engines of growth has been less relevant than in the previous group, and this may have, to a large extent, determined the relatively low intensity of supplier-producer interactions. The limited size of the home market, particularly in Austria and the Netherlands, constitutes an additional factor to explain the scarce importance of upstream linkages and scale intensive industries because the latter, by their own nature, necessitate a large market and a large plant size to exploit economies of scale and learning by doing mechanisms.

### **4A. Supplier-dominated industries in NIS with *strong* upstream linkages:**

Supplier-dominated sectors mostly innovate, by definition, by acquiring technologies, equipment and machinery from more technologically advanced industries. This trajectory of embodied technological change implies, of course, that the upstream linkages with the suppliers become a fundamental factor of competitiveness for these traditional industries. A large number of European economies in the sample seem to perform well in this respect (Germany, Norway, UK, France, Italy, Spain and Portugal), and are characterized by very high values of the variable SUPPLIERS (26,7%). This to a large extent reflects a pattern of technological and economic

specialization strongly oriented towards traditional and low-tech industries, a stronghold of the European manufacturing branch. The interaction between this type of sectoral trajectory and the related characteristics of national innovation systems may thus explain the positive performance and strong competitive position that some of these industries have achieved in the past few decades (e.g. textiles in Italy, see Malerba, 1993).

#### **4B. Supplier-dominated industries in NIS with *weak* upstream linkages:**

Differently from the previous group, supplier-dominated sectors in Sweden, Austria and the Netherlands are characterized by much weaker linkages between innovative firms and their technology providers (SUPPLIERS = 8,3%). Three possible factors may have determined a weaker intensity of upstream linkages in these national systems: first, the industrial structure and technological specialization patterns of these countries, less oriented towards traditional and low-tech manufacturing industries; second, the limited size of the home market, with the related demand constraints and greater exposure to foreign competition that it entails; third the country-specific industrial and innovation policies adopted by national governments, which in most cases have not actively sustained low-tech manufacturing industries but have rather focused on other core sectors (Verspagen, 2005).

< Table 4 here >

On the whole, the eight groups composing this refined version of Pavitt's taxonomy support the main idea put forward in the paper that national systems and sectoral patterns of innovation interact with each other, and that the aspects where these interactions are more evident are the intersectoral linkages between innovative firms, their suppliers, their users and the science system. These linkages affect, and are affected by, various characteristics of national systems, such as technological, scientific and economic specialization patterns and performance; industrial and innovation policies; home market and demand conditions; and other social, institutional and cultural factors affecting the degree of trust, cooperation and the systemicness of the national system.

Each of the original categories of Pavitt's taxonomy has been found to differ largely across countries in Europe, and has been endogenously divided into two separate sub-

categories: one where the cumulative interaction between national and sectoral systems supports and strengthens intersectoral knowledge exchanges, and another where the pattern is rather vicious and static, resulting in much weaker vertical linkages. The refined taxonomy, in a nutshell, shows that sectoral systems must be supported by and interact with their respective national systems in order to become industrial leaders (Mowery and Nelson, 1999). Intersectoral linkages and domestic knowledge flows are fundamental aspects to sustain the competitiveness and performance of sector- and country-specific technological trajectories.

## **5 Conclusions**

Studies of innovation systems have rapidly flourished in the last couple of decades. Different strands of research have investigated the patterns and dynamics of systems of innovation at different levels of analysis, and particularly the national (Balzat and Hanusch, 2004; Edquist, 2005) and the sectoral ones (Malerba, 2005 and 2006). Studies of both national and sectoral systems have greatly enriched our understanding of the characteristics, functioning and systemic properties of the innovative process. An important aspect that has not yet received the attention it would deserve, however, refers to the interactions between the meso and the macro levels in innovation systems. This paper has presented an attempt to shed new light on this unexplored issue, and it has thus investigated and discussed the relationships between national systems and sectoral patterns of innovation.

The study has been empirical in nature, and it has carried out a cross-sector cross-country statistical analysis of European innovation systems based on the CIS-SIEPI database, which contains CIS2 data on the innovative activity of 22 manufacturing sectors in ten European countries. The analysis has proceeded in three steps. First, it has tested the validity of Pavitt's (1984) taxonomy for our cross-sectional sample through a multinomial logit estimation (section 2). Second, by using 2-way ANOVA tests, it has investigated the cross-country variability of the sectoral trajectories originally identified by Pavitt along various dimensions, as well as the significance of a factor of interaction between national systems and sectoral patterns (section 3). Finally, it has carried out a classification and regression tree analysis in order to identify the various sector- and country-specific technological trajectories that

characterize European innovation systems, and, based on that, it has proposed a refinement of Pavitt's taxonomy (section 4).

The results of the empirical analysis can be briefly summarized as follows.

(i) There exists a large cross-country variability in all four sectoral technological trajectories identified by Pavitt, due to the great differences among national innovation systems. The different statistical techniques used (MNL estimations, ANOVA, and CART) all point out the relevance of the cross-country dimension.

(ii) There is evidence that the interaction between national systems and sectoral patterns of innovation constitutes an independent source of variability in European manufacturing industries. This is indicated by the interaction term in the 2-way ANOVA test (section 3), which turns out to be strong and significant for the variables measuring vertical linkages and systemic relationships between innovative firms, the users, the suppliers and the public science system.

(iii) When we focus on the latter set of factors, each category of Pavitt's taxonomy can be divided into two sub-categories: one where the cumulative interaction between national and sectoral systems supports and strengthens intersectoral knowledge exchanges, and another where the pattern is rather vicious and static, resulting in much weaker vertical linkages. This pattern has not been exogenously imposed or assumed, but it has rather emerged endogenously as a result of the classification and regression tree algorithm (see section 4, and Appendix 2).

These results lead, therefore, to the identification of eight sector- and country-specific technological trajectories in European manufacturing industries. This refinement of Pavitt's taxonomy supports the main idea put forward in the paper that national systems and sectoral patterns of innovation interact with each other, and that the aspects where these interactions are more evident are the intersectoral linkages between innovative firms, their suppliers, their users and the science system. These linkages affect, and are affected by, various characteristics of national systems, such as their technological, scientific and economic specialization patterns and performance; industrial and innovation policies; home market and demand conditions; and other social, institutional and cultural factors affecting the degree of trust, cooperation and the systemicness of the national system.

On the whole, the paper has constituted an attempt to shed new light on an unexplored issue, namely the interactions between national systems and sectoral patterns of innovation. The complex nature of this topic and the lack of previous studies

investigating it, however, make it extremely difficult to obtain clear-cut and conclusive results. Therefore, the overall contribution of the paper is not to provide definitive answers, but rather to open up new questions and to point to a new direction of research in the innovation system literature. We now conclude by pointing out more explicitly some major limitations of the study and, relatedly, some possible future extensions of this line of research.

First, the empirical evidence provided by the paper on the interactions between sectoral and national systems is suggestive, but the empirical analysis does not properly constitute a statistical test of these mutual relationships and of the intensity of their different mechanisms and channels. The static nature of the CIS data used in this paper, in fact, has not made it possible to carry out a thorough test of the dynamic and cumulative relationships between the meso and the macro level in innovation systems. The use of different data sources, such as R&D and patent data for longer time spans, would make it feasible to derive more robust and more conclusive statistical results on the interactions between sectoral and national systems.

Second, the empirical analysis has been limited to innovation patterns in manufacturing industries, and it has neglected the service sectors (due to a lack of relevant data for services). However, the latter constitute a large and increasingly dynamic branch of the European economy. Some very advanced knowledge intensive business services (KIBS), in particular, assume a fundamental role as providers of technologies and competencies to manufacturing industries (Miles, 2005; Castellacci, 2007b). Therefore, future extensions of this line of research should include services in the conceptualization of intersectoral linkages, and investigate their role in the meso-macro interaction.

Third, the CIS data that we have used do not make it possible to distinguish between the domestic *versus* the foreign nature of intersectoral linkages, and this is another limitation of the analysis carried out in this paper. The use of different data sources, where the geographical direction of intersectoral linkages could be measured, would make it possible to overcome this problem, and to investigate whether upstream and downstream linkages are indeed prevalently intra-national and domestic in nature, as the national innovation systems literature would suggest, or if, on the contrary, foreign linkages and the international diffusion of advanced knowledge play a more relevant role in the process of interaction between national systems and sectoral patterns of innovation.

Finally, the theoretical interpretation discussed in the paper has provided a cumulative and path-dependent view of the interactions between national and sectoral systems. The paper has argued that sectoral trajectories are reinforced (or weakened) over time by the characteristics of national systems, and that the latter, in turn, are reproduced and strengthened by the sectoral specificities of each country. It is important to acknowledge, though, that such a path-dependent and cumulative view should in the future be refined, and complemented by an investigation of the emergence of new technological paradigms and the diffusion of new trajectories that may co-exist, compete and eventually substitute for the old ones. The interaction between national and sectoral systems is not only about cumulativeness and path-dependency, but about novelty and change as well.

### **Appendix 1: The dataset and the sectoral classification**

The empirical analysis carried out in this paper has made use of the CIS-SIEPI database. This contains data from the *Second Community Innovation Survey* (1994-1996) on innovative activities of manufacturing industries in 10 European countries (Germany, Spain, France, Italy, Netherlands, Norway, Portugal, Sweden, UK and Austria). Compared to other CIS-related data sources (e.g. Eurostat), the CIS-SIEPI database contains 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 and to shed new light on sectoral patterns of innovation in Europe.<sup>12</sup>

In the empirical analysis, the 22 manufacturing industries have been assigned to the four categories of Pavitt's taxonomy by following Pavitt's (1984) original paper, as well as other subsequent empirical analyses that have made use of the taxonomy (Begg et al., 1999; Laursen and Meliciani, 2000; Marsili and Verspagen, 2002). The sectoral classification used in the paper is then the following.

*Specialized suppliers*: Machinery and equipment; medical and optical precision instruments.

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<sup>12</sup> The CIS-SIEPI database has been constructed as a result of the EU-funded SIEPI project ("The Structure of Innovation and Economic Performance Indicators"). The dataset contains CIS2 data at a higher level of sectoral disaggregation because the data have been obtained directly from national sources (i.e. from the statistical offices of the ten countries included in the database).



*Science-based*: Electrical; radio and TV; office, accounting and computing; chemicals; coke, refined petroleum products and nuclear fuel.

*Scale intensive*: Motor vehicles and trailers; other transport; rubber and plastics; basic metals; fabricated metal products; food and beverages.

*Supplier-dominated*: Textiles; wearing; leather and footwear; wood and related; pulp and paper; printing and publishing; other non-metallic mineral products; furniture; recycling.

The industries assigned to each of the four categories are consistent with previous works (see Laursen and Meliciani, 2000, Appendix 1). The only exception refers to the sector coke, refined petroleum products and nuclear fuel. We have decided to include it in the *science-based* category because: (i) there exists a significant scientific component in the production of nuclear fuel; (ii) the industry is characterized by large firms (as measured by our variable SIZE), which is one of the main characteristics of science-based sectors; (iii) the interactions between University and innovative firms are strong (in terms of our variable SCIENCE); and (iv) the industry is closely related and to some extent similar to the science-based chemicals sector (see Marsili and Verspagen, 2002).

## **Appendix 2: The CART methodology**

The *classification and regression tree algorithm* (CART) is a flexible non-parametric method of multivariate analysis (Breiman et al., 1984). It can be used for classifying a set of N cases into J categories based on a vector X of characteristics, or, alternatively, for predicting to which category a case belongs based on its vector X of characteristics.

The dependent variable in CART is categorical ( $j = 1$  to  $J$ ), while the explanatory variables  $X_i$  ( $i = 1$  to  $M$ ) can be both categorical and scale. The general idea of CART is to construct a hierarchical classification of cases, where each step of the algorithm splits a group of cases into two sub-groups (*nodes*) based on one single predictor variable  $X_i$ . The CART algorithm can be described as follows.

(1) The initial node (*root node*) comprises all N cases in the sample. It is split into two nodes,  $N_1$  and  $N_2$ , on the basis of the predictor variable  $X_i$  that makes it possible to achieve the best split (searching among all possible splits, and all predictor variables

used as inputs in the analysis). The criterion to search for the best split is to reduce the node's *impurity measure*, i.e. to reduce the number of cases not belonging to a given category. A node is *pure* when all cases belonging to it refer to the same category. The two most used criteria for splitting are the *Gini* and the *Twoing* methods. The results presented in section 4 are based on the former.

(2) The same splitting rule is subsequently applied to all successive non-terminal nodes. A node is *terminal* when it is not possible to improve the misclassification rate by splitting it further into two subnodes. The resulting tree,  $T_{\max}$ , tends to be very large, because no cost for splitting has initially been specified. This means that splitting cases is costless, and that the tree will thus tend to have many branches and several terminal nodes.

(3) The tree  $T_{\max}$ , therefore, does not provide either a correct idea of the right-sized tree, or an accurate and honest estimate of its misclassification rate. For this reason, the tree must be *pruned*, i.e. the branches that are superfluous must be cut. This is achieved in two ways. First, the algorithm specifies costs associated with each successive split, so that the higher the number of splits, the greater the overall cost. Second, the CART selects the best pruned subtree among all possible pruned subtrees. This selection is obtained by using two alternative methods: (i) *test sample estimates*, where a new sample is used to assess the precision of each subtree obtained through the analysis of the learning sample (this is the preferred method when a large sample is considered); (ii) *v-fold cross-validation*, where the learning sample is partitioned into  $V$  equal parts, and the  $v_{\text{th}}$  fraction is used to evaluate the precision of the  $(1-v)_{\text{th}}$  larger part (this method leads to better results in relatively small samples, and we have therefore used that in our analysis). Both criteria lead to an estimation of the number of misclassified cases, so that the best pruned subtree is the one that minimizes the estimated misclassification rate.

The classification tree diagram reported in Figure 2 (section 4) is the final result of the CART algorithm, and represents, therefore, the best pruned subtree. The right tree size, i.e. the number of branches and terminal nodes described in table 4, has therefore been found out *endogenously* by the algorithm through an extensive examination of all possible splitting conditions at each step, and all possible pruned subtrees.

## References

Andersen, E. S. (1992): “Approaching national systems of innovation from the production and linkage structure”, in B.A. Lundvall (Eds.), *National Systems of Innovation: Towards a Theory of Innovation and Interactive Learning*, Pinter Publishers, London.

Archibugi, D. (2001): “Pavitt’s taxonomy sixteen years on: a review article”, *Economics of Innovation and New Technology*, 10 (5): 415-425.

Archibugi, D. and Pianta, M. (1994): “Aggregate convergence and sectoral specialization in innovation”, *Journal of Evolutionary Economics* (1994) 4, pp. 17-33.

Balzat, M. and Hanusch, H. (2004): “Recent trends in the research on national innovation systems”, *Journal of Evolutionary Economics* (2004) 14: 197-210.

Balzat, M. and Pyka, A. (2006): “Mapping national innovation systems in the OECD area”, *International Journal of Technology and Globalisation*, 2 (1/2): 158-176.

Begg, I., Dalum, B., Guerrieri, P., and Pianta, M. (1999): “The impact of specialization in Europe”, in J. Fagerberg, P. Guerrieri and B. Verspagen (Eds.), *The Economic Challenge for Europe – Adapting to Innovation Based Growth*, Edward Elgar, Cheltenham.

Breiman, L., Friedman, J., Olshen, R. and Stone, C. (1984): *Classification and Regression Trees*, Wadsworth, Belmont, California.

Castellacci, F. (2007a): “Evolutionary and new growth theories. Are they converging?”, *Journal of Economic Surveys*, 21 (3): 585-627.

Castellacci, F. (2007b): “Technological paradigms, regimes and trajectories: manufacturing and service industries in a new taxonomy of sectoral patterns of innovation”, *Research Policy* (second revised version resubmitted).

Castellacci, F. (2007c): “Technological regimes and sectoral differences in productivity growth”, *Industrial and Corporate Change*, 16 (6): 1105-1145.

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

Dopfer, K., Foster, J. and Potts, J. (2004): “Micro-meso-macro”, *Journal of Evolutionary Economics* (2004) 14: 263-279.

Dosi, G. (1988): “Sources, procedures, and microeconomic effects of innovation”, *Journal of Economic Literature*, XXVI: 1120-1171.

Edquist, C. (1997): *Systems of Innovation: Technologies, Institutions and Organisations*, Pinter, London and Washington.

Edquist, C (2005): “Systems of innovation: perspectives and challenges”, in J. Fagerberg, D. C. Mowery and R. R. Nelson (Eds.), *The Oxford Handbook of Innovation*, Oxford University Press, Oxford.

Evangelista, R. (1999): *Knowledge and Investment. The Sources of Innovation in Industry*, Edward Elgar, Cheltenham.

Evangelista, R. and Mastostefano, V. (2006): “Firm size, sectors and countries as sources of variety of innovation”, *Economics of Innovation and New Technology*, 15 (3): 247-270.

Fagerberg, J. (1995): “User-producer interaction, learning and comparative advantage”, *Cambridge Journal of Economics*, 19: 243-256.

Fai, F. and von Tunzelmann, N. (2001): “Industry-specific competencies and converging technological systems: evidence from patents”, *Structural Change and Economic Dynamics*, 12: 141-170.

Freeman, C. (1987): *Technology Policy and Economic Performance: Lessons from Japan*, Pinter, London.

Laursen, K. (2000): “Do export and technological specialisation patterns co-evolve in terms of convergence or divergence? Evidence from 19 OECD countries, 1971-1999”, *Journal of Evolutionary Economics* (2000) 10, pp. 415-436.

Laursen, K. and Meliciani, V. (2000): “The importance of technology based inter-sectoral linkages for market share dynamics”, *Weltwirtschaftliches Archiv*, 136 (4).

Laursen, K. and Meliciani, V. (2002): “The relative importance of international *vis-à-vis* national technological spillovers for market share dynamics”, *Industrial and Corporate Change*, 11 (4): 875-894.

Laursen, K. and Salter, A. (2005): “The fruits of intellectual production: economic and scientific specialisation among OECD countries”, *Cambridge Journal of Economics*, 29, pp. 289-308.

Lundvall, B.A. (1992) *National Systems of Innovation: Towards a Theory of Innovation and Interactive Learning*, Pinter Publishers, London.

Lundvall, B. A. and S. Borrás (2005): “Science, technology and innovation policy”, in J. Fagerberg, D. C. Mowery & R. R. Nelson (Eds.), *The Oxford Handbook of Innovation*, Oxford University Press, Oxford.

Malerba, F. (1993): “The national system of innovation: Italy”, in Nelson, R. (Ed.), *National Innovation Systems: A Comparative Analysis*, Oxford University Press, New York and Oxford.

Malerba, F. (2006): “Innovation and the evolution of industries”, *Journal of Evolutionary Economics*, 16 (1-2): 3-23.

Malerba, F. (2005): "Sectoral systems: how and why innovation differs across sectors", in J. Fagerberg, D. C. Mowery & R. R. Nelson (Eds.), *The Oxford Handbook of Innovation*, Oxford University Press, Oxford.

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

Malerba, F. and Montobbio, F. (2003): "Exploring factors affecting international technological specialization: the role of knowledge flows and the structure of innovative activity", *Journal of Evolutionary Economics* (2003) 13: 411-434.

Marsili, O. and Verspagen, B. (2002): "Technology and the dynamics of industrial structure: an empirical mapping of Dutch manufacturing", *Industrial and Corporate Change*, vol.11 (4), pp.791-815.

Miles, I. (2005): "Innovation in services", in J. Fagerberg, D. C. Mowery & R. R. Nelson (Eds.), *The Oxford Handbook of Innovation*, Oxford University Press, Oxford.

Mowery, D. and Nelson, R. (1999): *The Sources of Industrial Leadership*, Cambridge University Press, Cambridge.

Mowery, D. and Sampat, B. (2005): "Universities in national innovation systems", in J. Fagerberg, D. C. Mowery & R. R. Nelson (Eds.), *The Oxford Handbook of Innovation*, Oxford University Press, Oxford.

Murmann, J. P. and Homburg, E. (2001): "Comparing evolutionary dynamics across different national settings: the case of the synthetic dye industry, 1857-1914", *Journal of Evolutionary Economics* (2001) 11: 177-205.

Narula, R. (2002): "Innovation systems and 'inertia' in R&D location: Norwegian firms and the role of systemic lock-in", *Research Policy*, 31 (5): 795-816.

Nelson, R.R. (ed.) (1993): *National Innovation Systems: A Comparative Analysis*. Oxford University Press, New York and Oxford.

Nelson, R. and Winter, S. (1977): "In search of a useful theory of innovation", *Research Policy*, 6: 36-76.

Nelson, R. and Winter, S. (1982): *An Evolutionary Theory of Economic Change*, The Belknap Press of Harvard University Press, Cambridge, USA.

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

Peracchi, F. (2001): *Econometrics*, Wiley, Chichester.

Porter, M. (1990): *The Competitive Advantage of Nations*, Macmillan, London.

Powell, W. and Grodal, S. (2005): “Networks of innovators”, in J. Fagerberg, D. C. Mowery & R. R. Nelson (Eds.), *The Oxford Handbook of Innovation*, Oxford University Press, Oxford.

Scott Long, J. (1997): *Regression Models for Categorical and Limited Dependent Variables. Advanced Quantitative Techniques in the Social Sciences, Volume 7*, Sage Publications.

Tidd, J., Bessant, J. and Pavitt, K. (1997): *Managing Innovation – Integrating Technological, Market and Organizational Change*, Wiley, Chichester.

Verspagen, B. (2005): “The Netherlands Innovation system”, in C. Edquist and L. Hommen (Eds.), *Globalization and National Systems of Innovation – A Comparative Study of Ten Small Countries in Europe and Asia*, Edward Elgar, Cheltenham, forthcoming.

Table 1: Results of the multinomial logit regression analysis for Pavitt's taxonomy, *model without country dummies*

Dependent variable "Pavitt's taxonomy":  $\{Y=j\}$ ,  
 where  $j = 1$  for specialized suppliers;  $j = 2$  for science-based;  $j = 3$  for scale intensive;  
 $j = 4$  for supplier-dominated industries.

		Specialized suppliers	Science based	Scale intensive	Likelihood ratio test
Estimated logit coefficients (Wald statistic between parenthesis)	Constant	-6,48 (5,33)***	-2,14 (1,67)	-0,44 (0,17)	7,51*
	Internal sources of technology creation	0,12 (11,29)***	0,05 (6,72)***	0,02 (1,78)	19,06***
	Science-based sources of innovation	0,04 (0,03)	0,40 (8,71)***	0,21 (3,78)**	12,93***
	New processes vs. new products	-12,27 (9,67)***	-5,56 (5,15)**	-1,73 (1,31)	15,72***
	Size of innovators	-2,03 (2,49)	1,95 (5,26)**	1,12 (4,06)**	18,57***
	User-producer interactions	0,06 (4,12)**	0,008 (0,17)	0,018 (1,46)	6,09
	Interactions with the suppliers	-0,03 (0,31)	-0,08 (3,20)*	-0,05 (2,96)*	4,58
Pseudo R-squared	Cox and Snell	0,61			
	Nagelkerke	0,66			
Classification table	Specialized suppliers	40,0%			
	Science based	70,4%			
	Scale intensive	51,1%			
	Supplier dominated	75,0%			
	Overall correctly predicted percentage	61,8%			

\*\*\* Significance at the 0,01 level; \*\* Significance at the 0,05 level; \* Significance at the 0,10 level

Table 2: Results of the multinomial logit regression analysis for Pavitt's taxonomy, *model with country dummies*

Dependent variable "Pavitt's taxonomy":  $\{Y=j\}$ ,  
 where  $j = 1$  for specialized suppliers;  $j = 2$  for science-based;  $j = 3$  for scale intensive;  
 $j = 4$  for supplier-dominated industries.

		<b>Specialized suppliers</b>	<b>Science based</b>	<b>Scale intensive</b>	<b>Likelihood ratio test</b>
<b>Estimated logit coefficients (Wald statistic between parenthesis)</b>	<b>Internal sources of technology creation</b>	0,31 (14,57)***	0,14 (9,58)***	0,04 (2,63)	35,62***
	<b>Science-based sources of innovation</b>	-0,46 (1,54)	0,31 (1,97)	0,13 (0,71)	11,04**
	<b>New processes vs. new products</b>	-16,97 (5,45)**	-3,74 (0,90)	-0,13 (0,003)	10,26**
	<b>Size of innovators</b>	-3,02 (2,61)	1,80 (2,15)	1,52 (4,74)**	16,26***
	<b>User-producer interactions</b>	-0,04 (0,14)	0,02 (0,11)	0,07 (2,44)	4,42
	<b>Interactions with the suppliers</b>	-0,13 (0,83)	-0,33 (8,43)***	-0,12 (4,14)**	12,64***
	<b>France</b>	-15,10 (6,76)***	-5,45 (1,83)	-2,98 (1,55)	9,14**
	<b>Italy</b>	-7,15 (2,18)	1,21 (0,12)	0,39 (0,03)	4,59
	<b>Netherlands</b>	-14,34 (7,94)***	-6,18 (3,77)*	-1,34 (0,81)	12,44***
	<b>Norway</b>	-3,18 (0,165)	-0,43 (0,06)	-2,12 (0,32)	0,54
	<b>Portugal</b>	-0,50 (0,006)	0,43 (0,01)	-0,86 (0,08)	0,17
	<b>Sweden</b>	-7,81 (1,17)	-6,50 (1,64)	-5,18 (2,33)	2,91
	<b>UK</b>	-1,79 (0,07)	1,13 (0,06)	-1,26 (0,13)	0,69
<b>Austria</b>	-7,49 (1,21)	-7,13 (2,22)	-4,74 (2,36)	3,29	

\*\*\* Significance at the 0,01 level; \*\* Significance at the 0,05 level; \* Significance at the 0,10 level



Table 2 (continued):

<b>Pseudo R-squared</b>	<b>Cox and Snell</b>	0,78
	<b>Nagelkerke</b>	0,83
<b>Classification table</b>	<b>Specialized suppliers</b>	73,3%
	<b>Science based</b>	70,4%
	<b>Scale intensive</b>	55,6%
	<b>Supplier dominated</b>	79,5%
	<b>Overall correctly predicted percentage</b>	68,7%

Table 3: Results of 2-way analysis of variance (ANOVA) for each of Pavitt's measured characteristics

<b>Variable</b>		<b>Factor <i>Pavitt</i></b>	<b>Factor <i>Country</i></b>	<b>Interaction <i>Pavitt*Country</i></b>
<b>Internal sources of technology creation</b>	Partial Eta Squared	0,50	0,37	0,07
	F-ratio	57,63***	10,94***	0,49
<b>Science-based sources of innovation</b>	Partial Eta Squared	0,29	0,31	0,44
	F-ratio	21,58***	8,08***	4,66***
<b>New processes vs. new products</b>	Partial Eta Squared	0,21	0,24	0,10
	F-ratio	14,93***	5,79***	0,71
<b>Size of innovators</b>	Partial Eta Squared	0,29	0,14	0,11
	F-ratio	15,70***	2,69**	0,64
<b>User-producer interactions</b>	Partial Eta Squared	0,19	0,75	0,29
	F-ratio	13,73***	62,00***	2,76***
<b>Interactions with the suppliers</b>	Partial Eta Squared	0,21	0,48	0,27
	F-ratio	15,79***	18,16***	2,42***

Figure 1a: The cross-country variability of science-based sources of innovation

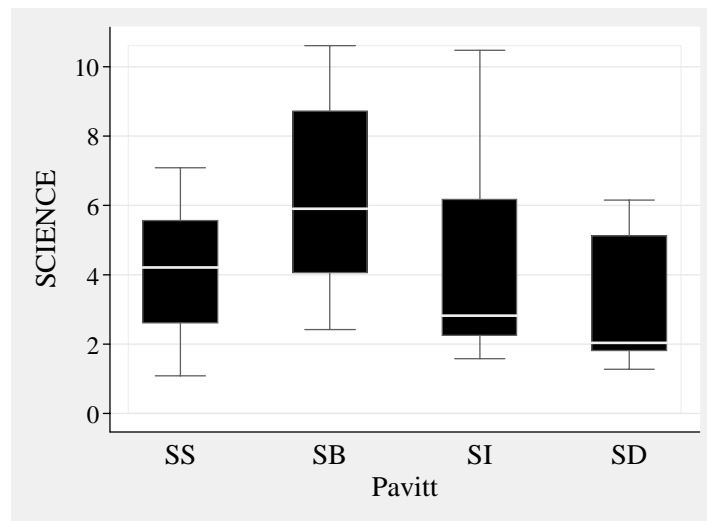


Figure 1b: The cross-country variability of user-producer interactions (USERS)

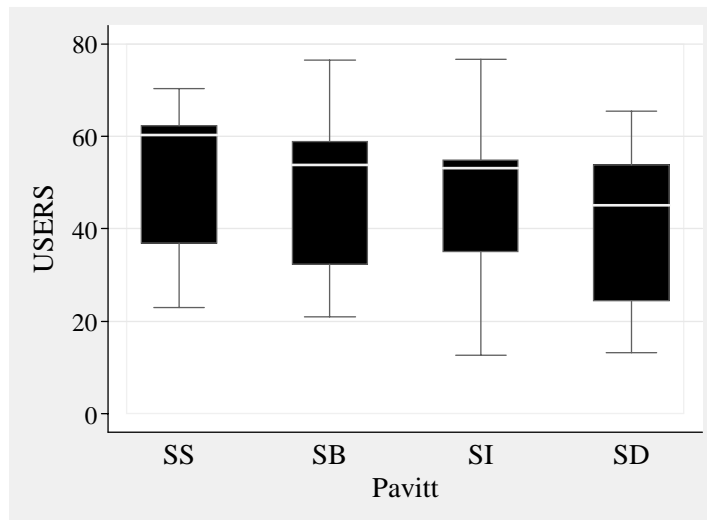


Figure 1c: The cross-country variability of the interactions with the suppliers (SUPPLIERS)

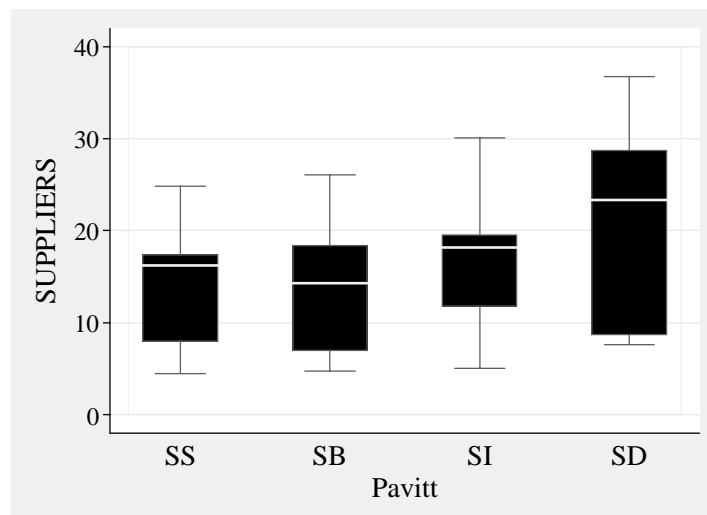
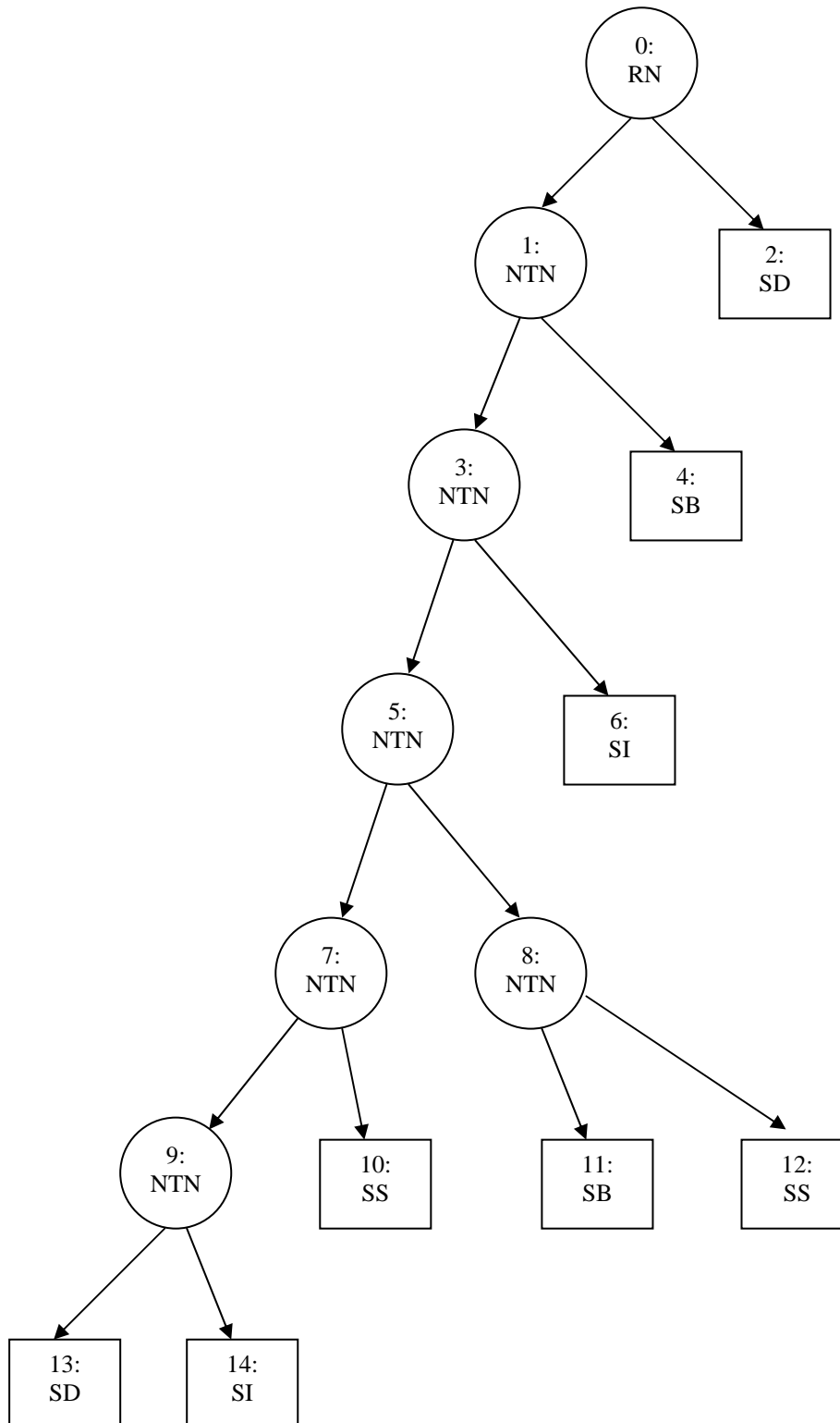


Figure 2: A refinement of Pavitt's taxonomy – The classification tree diagram



*Legend:*  
 RN: Root node; NTN: Non-terminal node;  
 SS: Specialized suppliers; SB: Science-based; SI: Scale intensive; SD: Supplier-dominated

Table 4: A refinement of Pavitt's taxonomy – Characteristics of the eight terminal nodes resulting from the classification tree analysis

Industry group	Terminal node	Splitting conditions	Countries included in the industry group	Characterizing feature (average by country)
1A. Specialized suppliers in NIS with <i>strong</i> downstream linkages	12	USERS > 60,1 3,4 < SCIENCE < 7,8 SUPPLIERS < 17,5	Austria, Germany, Norway, Sweden, Spain, UK	User-producer interactions: 63,6%
1B. Specialized suppliers in NIS with <i>weak</i> downstream linkages	10	SCIENCE < 3,4 14 < SUPPLIERS < 17,5	France, Italy, Netherlands, Portugal	User-producer interactions: 32,2%
2A. Science-based in NIS with <i>strong</i> university-industry links	4	SCIENCE > 7,8 SUPPLIERS < 22,9	Austria, Germany, Norway, Sweden	Science-based sources of innovation: 9,2%
2B. Science-based in NIS with <i>weak</i> university-industry links	11	3,4 < SCIENCE < 7,8 USERS < 60,1 SUPPLIERS < 17,5	France, Italy, Netherlands, Portugal, Spain, UK	Science-based sources of innovation: 4,2%
3A. Scale intensive in NIS with <i>strong</i> upstream linkages	6	17,5 < SUPPLIERS < 22,9 SCIENCE < 7,8	France, Germany, Italy, Norway, Portugal, Sweden, UK	Interactions with the suppliers: 20,7%
3B. Scale intensive in NIS with <i>weak</i> upstream linkages	14	SUPPLIERS < 14 2,1 < SCIENCE < 3,4	Austria, Netherlands, Spain	Interactions with the suppliers: 8,2%
4A. Supplier-dominated in NIS with <i>strong</i> upstream linkages	2	SUPPLIERS > 22,9	France, Germany, Italy, Norway, Portugal, Spain, UK	Interactions with the suppliers: 26,7%
4B. Supplier-dominated in NIS with <i>weak</i> upstream linkages	13	SUPPLIERS < 14 SCIENCE < 2,1	Austria, Netherlands, Sweden	Interactions with the suppliers: 8,3%