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# Innovation, international R&D Spillovers and the sectoral heterogeneity of knowledge flows[♦].

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Abstract

This paper analyses the relative effects of national and international, intra-sectoral and inter-sectoral spillovers on innovative activity in six large, industrialized countries (France, Germany, Italy, Japan, UK and US) over the period 1981-1995. We use patent applications at the European Patent Office to measure innovation and their citations to trace knowledge flows within and across 135 narrowly defined technological fields. We find that, in addition to international ones, intra-sectoral spillovers are an important determinant of innovation.

JEL Codes: F0, O3, R1
Keywords: R&D spillovers, Knowledge flows, Patent citations.

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## 1 Introduction

In the past two decades macroeconomic models have underlined the importance of knowledge spillovers and externalities and described how spillovers increase innovative activity and productivity (e.g. Rivera-Batiz and Romer, 1991; Grossman and Helpman, 1991). These models have stimulated a number of empirical contributions that have examined how ideas can be transferred and measured the economic impact of knowledge spillovers. Advancements on the issue have followed different routes. The trade and technology literature has mostly analyzed the extent and economic relevance of trade related international knowledge spillovers. (e.g. Coe and Helpman 1995, Luintel and Khan, 2004). Other authors have used firm level data focusing on localized knowledge spillovers (Jaffe et al. 1993). Different methodologies and techniques have been used to measure different types of spillovers. As a consequence of all these contributions, there is now the recognition of the local character of knowledge spillover and the need to disentangle national from international spillovers.

This paper adds to the exiting literature by examining the sectoral and technological heterogeneity of spillovers. We claim that inventors mainly benefit from spillovers that come from other inventions in the same technology and the same sector. There are few works on international R&D spillovers that focus on spillovers across sectors (e.g. Keller, 2002; Frantzen, 2002; Park, 2004). However these studies work at a very high level of aggregation and examine the impact of spillovers on Total Factor Productivity (TFP).

Our analysis is at a very disaggregated level, concerning clearly defined technological fields that correspond to product groupings. We use a multi-country panel of 135 small technological fields within three broad sectors (chemicals, electronics and machinery) to measure and compare different types of R&D spillovers. We distinguish between spillovers that occur within or across the 135 technological fields, and that are national or international.

Using a knowledge production function we develop an empirical model to estimate the different types of spillovers in a unified framework. We address the issue of the sectoral heterogeneity of knowledge spillovers by examining their effects on knowledge production. We use patent applications and citations at the European Patent Office (EPO), and R&D data for six large, industrialized countries (Us, Japan, Germany, France, UK and Italy) over the period 1981-1995. Patent applications serve as a measure of innovative output, while their citations are here used to measure the direction and intensity of knowledge flows within and across technological fields and national boundaries.

We apply techniques of panel cointegration estimation to evaluate the impact of different types of spillovers. We show that there is a long-run relationship between the stock of generated ideas, R&D and spillovers even though each variable is non-stationary. In each sector there exists a linear combination of the stock of accumulated knowledge, R&D expenditures, domestic and international R&D spillovers that is stationary and the series are cointegrated. Our main finding regards the extremely relevant role of intra-sectoral spillovers for innovative activities in advanced countries. In addition, the relevant role of international R&D spillovers is confirmed. However when very disaggregated technological fields are considered, the estimated international R&D spillover effect is larger than previously considered. We also show that the types of knowledge spillovers differ between the chemical, mechanical and electronic sectors.

The paper is organized as follows. Section 2 presents an overview of the theoretical background of the paper and discusses the evidence on knowledge spillovers at the macro and micro level. In Section 3 we present the empirical model that illustrates the relationship between innovation and the different types of spillovers. Section 4 presents the data and provides some descriptive evidence. In Section 5 we report the unit root tests, the estimation of the cointegration vector and comment the estimation results. In Section 6 we draw our conclusions.

## 2. Knowledge production and spillovers

This paper studies the impact of knowledge spillovers directly on the determinants of innovative activity using a knowledge production function (KPF)

(Pakes and Griliches; 1980)[1]. The KPF maps research efforts into new knowledge, often proxied by patent counts (Griliches, 1990). Research efforts include own R&D resources, but also external sources of knowledge in terms of knowledge spillovers. Indeed, to a certain extent knowledge can be transferred from one firm or country to another (e.g. it can be codified or simply employees move from one firm/country to another as they change job). Because of its (partial) public good nature, knowledge produced by one economic agent may spill over to other agents, who can subsequently employ it to produce new knowledge[2].

There is a large consensus that estimated R&D spillovers effects are significant and positive[3]. Spillovers are typically measured with reference to a pool of available external knowledge, obtained from the R&D capital of potential sources (e.g. other firms, regions or countries) At the micro level some authors have underlined the role of technological proximity between companies. Jaffe (1986, 1988) finds a positive spillover effect for firms that are technologically similar. He characterizes each firm by a vector of patents in a number of technological classes and then uses such vectors to build a symmetric proximity index between firms. Cincera (1997) using a sample of 181 firms from US, Europe and Japan in the period 1983–1991, finds positive effects for R&D spillovers within broad manufacturing sectors.

At the same time knowledge spillovers tend to be geographically localized. Maruseth and Verspagen (2002) use a cross-section of 112 European regions to show that patent citations (at the EPO) have a propensity to be geographically localised. Similar results, also using EPO citations, are obtained by Bottazzi and Peri (2003). Peri (2005) shows also that knowledge flows tend to be geographically localized, using the

[1] There is a great number of articles that measure the impact of *trade related* international R&D spillovers on total factor productivity (TFP) (e.g. Coe and Helpman, 1995; Eaton and Kortum, 1996; Coe et al. 1997; Keller 1998; Kao et al. 1999; Edmond 2001; Frantzen 2002; Park 2004; Luintel and Kahn, 2004). In general these papers support the idea that trade related international spillovers affect TFP. Though some doubts are cast by Kao et al. (1999) and Edmond (2001) that use panel cointegration econometrics and a great heterogeneity is underlined by Luintel and Kahn (2004) that suggest that data from different countries cannot be pooled. These papers differ from our work in two major respects. First they measure TFP elasticity to international spillovers. We estimate a (spillover-augmented) knowledge production function. Second, they focus on trade related international R&D spillovers. We use patent citations that are more suited for the estimation of the probability to patent.

[2] Breschi and Lissoni (2004) survey the recent debate on the sources and nature of knowledge spillovers.

[3] An extensive review of this lively area of research can be found in Cincera and van Pottelsberghe de la Potterie (2001) and Wieser (2005).

NBER data on patents and patent citations from the US Patent and Trademark Office, for a panel of 113 European and North American regions over 22 years.

Knowledge flows cross also sector boundaries. Some studies show that inter-sectoral spillovers play a relevant role in explaining some economic variables like growth of total factor productivity, export performance and international technological specialization (Mohen, 1997; Verspagen, 1997; Malerba and Montobbio, 2003). Other authors like Bernstein (1988) and Bernstein and Nadiri (1988) use a different methodological framework and estimate cost functions for a sample of Canadian and US firms and for two-digit industry level data in the US. They find that inter-sectoral spillovers are extremely significant. Wieser (2005) summarizes a broad set of heterogeneous contribution to the literature and claims that inter-sectoral spillovers seem to be more significant than intra-sectoral even if it is impossible to directly compare intra-sectoral with inter-sectoral spillovers at the sector level because different studies measure spillovers in different ways and use different econometric strategies.

Some recent empirical works have shown that knowledge flows cross also national borders. Bottazzi and Peri (2007) show that internationally generated ideas affect significantly innovation in a country. They estimate a cointegration relation between the stock of knowledge of a country, its R&D resources and the stock of international knowledge and find that they move together in the long run. Their findings also confirm the relevant role of international spillovers. However also national spillovers are relevant. Branstetter (2001) uses a patent function to estimate firm level spillover. Based on a panel of 205 firms in five high R&D/sales ratio industries in the period 1985-1989, he provides strong evidence for Japanese intra-national knowledge spillovers and limited evidence that Japanese firms benefit from knowledge produced by American firms.

In sum, the overall assessment is that spillovers are local, that both national and international knowledge spillovers have a significant impact on firms' innovation activities, and that spillovers may come from firms which are active in different technologies. However estimates vary widely and it is difficult to consistently compare the relative impact of these different types of spillovers.

This paper explores spillovers that occur within and across narrowly defined technological fields/product groups. The use of such highly disaggregated fields is meant to reflect the idea that knowledge spillovers are technology specific as recognized by Atkinson and Stiglitz (1969) and Rosenberg (1976). Most of the times, technical change takes place in the proximity of the current techniques, through learning by doing (Arrow, 1962) and incremental search (Nelson and Winter, 1982). So the current set of techniques and the knowledge at the base of new ideas bind and constrain new advancements (Sutton, 1998) and knowledge itself is specific to the technological environment in which it is produced. For example, a firm doing R&D in technical and natural polymers produces new knowledge by using knowledge and technologies mostly related to those specific technical or natural polymers. But because technologies and sectors differ greatly in terms of knowledge required for innovation (Pavitt, 1984; Breschi et al. 2000), knowledge most of the times remains highly related to the specific technological field. A company doing R&D on lasers will produce new knowledge by using knowledge and technologies related to lasers which differ greatly from those related to natural polymers.

Machlup (1984) has forcefully pointed out that knowledge is dispersed in terms of agents and divided in terms of content, in this paper we add that this dispersion and division regards also technologies and sectors, and not just countries and geographical locations. Moreover knowledge advancements require that innovators have specific absorptive capabilities accumulated in the realm of the technologies and sectors where the spillovers come from (Cohen and Levinthal, 1989). So new ideas are highly affected by knowledge spillovers coming from sources of knowledge that are in the same technology or sector of the inventor, and require capabilities developed in that technology or sector for their absorption.

Therefore one would expect that intra-sectoral knowledge spillovers are particularly relevant for new knowledge production for the following reason. Knowledge spills over more easily within a sector than across sectors. Firms that do R&D in a technology or in a sector have a similar knowledge base. Therefore the knowledge that they produce is less costly and less difficult to transfer from one firm to another within a sector than knowledge produced in other sectors. One would also expect that this holds also for intra-sectoral international knowledge flows. And as a consequence of the sectoral and technological specificity of knowledge production one would expect also that differences exist in the relevance and types of spillovers.

This paper will proceed in sequential steps. It will first test the relevance of international spillovers and will try to confirm recent results (see Bottazzi and Peri, 2007). It will then move to assess the role of intra-sectoral spillovers and the differences in the typology of spillovers across sectors such as chemicals, electronics and machinery.

In this paper, we use patent citations to explore the relevance of knowledge flows, as other authors have done (e.g. Maruseth and Verspagen, 2002; Jaffe et al. 1993, Peri, 2005). In the patent documents citations are used by examiners and applicants to show the degree of novelty and inventive step of the claims of the patent. They are located in the patent document, usually by either the inventor's attorneys or by patent office examiners (depending upon national regulations) and, once published, provide a legal delimitation of the scope of the property right. Therefore citations identify the antecedents upon which the invention stands and, for this reason, they are increasingly used in economic research to gauge the intensity and geographical extent of knowledge spillovers (Griliches, 1990)[4]. Patent citations can therefore be considered a paper trail between the citing and the cited inventors (or institutions).

We use patents and patent citations from the European Patent Office (EPO). The EPO guidelines for patent examiners suggest to include all the technically relevant information within a minimum number of citations. Citations are, with few exceptions, added by the patent office examiners (EPO, 2005; Breschi and Lissoni, 2004)[5] when they draft their search report[6]. This reduces the probability to have citations that are erroneously or strategically included to deceive patent examiners.

[4] The use of patent citations as an index of knowledge flow has been validated by a survey of inventors (Jaffe et al. 2000, for the US Patent and Trademark Office) and corroborates substantial evidence on the type and nature of knowledge spillovers (e.g. Maruseth and Verspagen, 2002; Jaffe et al. 1993). In particular Jaffe et al. (2000) show that the likelihood of knowledge spillover is significantly higher if there is a citation; as a consequence they can be regarded as a signal for spillover (see also Trajtenberg, 1990).

[5] There are relevant differences between citation practices at the USPTO and EPO. In the US there is the 'duty of candor' rule, which imposes all applicants to disclose all the prior art they are aware of. Therefore many citations at the USPTO come directly from inventors, applicants and attorneys and are subsequently filtered by patent examiners.

[6] The search report at the EPO is a document, published typically 18 months after the application date, that has the main objective to discover the prior art relevant for determining whether the invention meets the novelty and inventive step requirements. It represents what is already known in the technical field of the patent application.

## 3 An empirical model for the patent equation

We build our model starting from a knowledge production function describing the production of technological output from R&D investment:

$$Q_{hit} = f(R_{hit}, \alpha, \nu_{hi}) = R_{hit}^{\alpha} \nu_{hi} \tag{3.1}$$

where $Q_{hit}$ is some latent measure of technological output in technological field $i$ ($i$ = 1, …, 135), country $h$ and period $t$, $R_{hit}$ measures the corresponding R&D investment, $\alpha$ represents the unknown technology parameter and $\nu_{hi}$ captures country and technological field specific effects (as, for example, the set of opportunity conditions).

We then assume that existing ideas and knowledge spillovers are important inputs in the creation of new ideas. Therefore, our latent measure of technological output is a function of a composite measure of research effort and we re-write equation (3.1) as:

$$Q_{hit} = \widetilde{R}_{hit}^{\alpha} \nu_{hi} \tag{3.2}$$

$$\widetilde{R}_{hit}^{\alpha} = R_{hit}^{\alpha_1} \cdot NS_{hit}^{\alpha_2} \cdot IS_{hit}^{\alpha_3} \cdot A_{hit}^{\alpha_4} \tag{3.3}$$

where $NS_{hit}$ and $IS_{hit}$ are measures for national and international spillovers, while $A_{hit}$ is the stock of cumulated knowledge generated by country $h$ in technological field $i$ at the beginning of period t.

Patents, $P_{hit}$, are a noisy indicator of technological output:

$$P_{hit} = Q_{hit} e^{\theta_{hi} t} u_{hi} \tag{3.4}$$

with $e^{\theta_{hi} t}$ accounting for possible trend in patenting (which might differ across countries and technological fields) and $u_{hi}$ for differences in country specific propensity to patent in each technological field. Combining (3.2) and (3.4) results in the following patent equation:

$$P_{hit} = \widetilde{R}_{hit}^{\alpha} e^{\theta_{hit}} \xi_{hi} \tag{3.5}$$

We cannot directly estimate (3.5) because we do not have the same level of sectoral aggeration for R&D and patent and citation data. In fact we use the R&D data of 15 manufacturing (ISIC) sectors[7] while we re-aggregate patents and patent citations into 135 technological fields. In order to deal with this, we make the following assumption:

$$R_{hit} = R_{hIt}^{\lambda} \varsigma_{hi} \quad \text{where} \quad i \in I \tag{3.6}$$

Hence, we assume that (the logarithm of) R&D expenditures within a technological field are a portion λ of (the logarithm of) R&D expenditures within the ISIC grouping the technological field belongs to. This portion is assumed to be the same for all technological fields: differences across them are accounted for by a fixed effect component, $\zeta_{hi}$. Using (3.3) and (3.6), equation (3.5) then becomes:

$$P_{hit} = R_{hIt}^{\lambda\alpha_1} \cdot NS_{hit}^{\alpha_2} \cdot IS_{hit}^{\alpha_3} \cdot A_{hit}^{\alpha_4} e^{\theta_{hit}} \varepsilon_{hi} \tag{3.7}$$

We trace knowledge flows using patent citations. National spillovers are measured in the following way:

$$NS_{hit} = \prod_{j \neq i} R_{hjt}^{nc_{hij}} \quad \text{with} \quad R_{hjt} = R_{hJt}^{\lambda} \mu_{hj} \tag{3.8}$$

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[7] The manufacturing sectors reported in Table A.1 in the Appendix. However given our focus on technological fields in chemicals, electronics and machinery sectors, only data for fifteen ISIC2 groupings have been used, as explained in the Appendix.

where $nc_{hij}$ is the relative number of citations from patents classified into technological field $i$ to patents classified into technological field $j$ and held by other firms in the same country $h$[8]. International spillovers are measured in a similar manner as:

$$IS_{hit} = \prod_{j} FR_{hjt}^{ic_{hij}} \tag{3.9}$$

where $ic_{hij}$ is the relative number of citations from patents held by firms in country $h$ and classified into technological field $i$ to patents held by firms in a different country and classified into technological field $j$. FR stands for foreign R&D and is defined as:

$$FR_{hjt} = \prod_{f \neq c} R_{fjt}^{rc_{hf}} \qquad \text{with } R_{fjt} = R_{fJt}^{\lambda} \mu_{fj} \tag{3.10}$$

where $rc_{hf}$ is the relative number of citations flowing from country $h$ to a foreign country, $f$, out of the total number of international citations made by patents held by firms in the home country.

The stock of cumulated knowledge is obtained by accumulating past patented ideas using the perpetual inventory method:

$$A_{hi,t+1} = P_{hit} + (1-\delta) A_{hit} \tag{3.11}$$

where δ is a constant depreciation rate. Similarly to Bottazzi and Peri (2007), we choose $\delta = 0.1$ and construct the variable $A_{hit}$ by setting the initial value of the knowledge stock at the following level:

$$A_{hi\,1981} = \frac{P_{hi\,1981}}{\left(\overline{g}_{hi} + \delta\right)} \tag{3.12}$$

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[8] $nc_{hij}$ is equal to the number of citations from patents classified into technological field $i$ to patents classified into technological field $j$ and held by to other national firms (i.e. excluding self citations) divided by the total number of national citations outflowing from field $i$. Note further that in (3.8) the

where $\overline{g}_{hi}$ is the growth rate of patenting in country $h$ technological field $i$ in the first five years of our sample and δ = 0.1, as specified above. Taking logs of (3.7), our patent function then becomes[9]:

$$ln\ P_{hit} = \lambda\alpha_1 r_{hIt} + \lambda\alpha_2 ns_{hit} + \lambda\alpha_3 is_{hit} + \alpha_4 a_{hit} + \theta_{hi} t + \xi_{hi} \quad (3.13)$$

where $r_{hIt} = ln\ R_{hIt}$ , $a_{hit} = \ln A_{hit}$ and

$$ns_{hit} = \sum_{j \neq i} nc_{hij} \ln R_{hJt} \quad (3.14)$$

$$is_{hit} = \sum_{j} ic_{hij} \sum_{f \neq h} rc_{hf} \ln R_{fJt} \quad (3.15)$$

The international spillover variable in (3.15) includes both intra-sectoral (within field) spillovers and inter-sectoral (between fields) spillovers. In particular, the first component is equal to:

$$istra_{hit} = \sum_{i} ic_{hii} \sum_{f \neq h} rc_{hf} \ln R_{fJt} \quad (3.16)$$

Note that, following Brandstetter (2001) we have only current R&D in the patent equation. This is because distributed lags on R&D induce a multicollinearity problem in

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product is over $j \neq i$ because spillovers within the same technological field are already included into the own R&D measure; put it differently, their effect cannot be distinguished from that of own R&D.

[9] Note that the individual effect in equation (3.12) include elements which involve summations of (weighted) individual effects components of other technological fields in both home and foreign countries. However, these summations are fixed in time for each '*hi*' hence we include them into an overall individual effect, $\xi_{hi}$ , without loss of generality. For this reason, fixed effects estimation methods are to be preferred to random effects methods which should account for the complex correlation across individuals (here: country/technological class pairs) in the variance covariance matrix.

the estimation, as noted by Hall et al. (1986). Furthermore, substantial evidence also suggests that new knowledge spills over rather quickly (Mansfield, 1985)[10].

Dividing equation (3.11) by $A_{hit}$ and re-arranging we obtain:

$$\frac{P_{hit}}{A_{hit}} = g_{hit}^{A} + \delta \qquad (3.17)$$

where $g_{hit}^{A}$ is the growth rate of the stock of knowledge in country $h$ and technological field $i$ in period $t$. Taking logs on both sides and substituting (3.13) into (3.17) we obtain the following relation:

$$ln\left(g_{hit}^{A} + \delta\right) = \lambda\alpha_1 r_{hIt} + \lambda\alpha_2 ns_{hit} + \lambda\alpha_3 is_{hit} + \left(\alpha_4 - 1\right)a_{hit} + \theta_{hit} + \xi_{hi} \qquad (3.18)$$

If knowledge creation converges to a deterministic balanced growth path, then $g_{hit}^{A} + \delta$ converges to a country-technology specific constant $g_{hi}^{A} + \delta$. Alternatively, if knowledge creation converges to a stochastic balanced growth path, then $g_{hit}^{A} + \delta$ converges to a trend stationary stochastic process. Equation (3.18) then represents the long-run relationship between $rd_{hIt}$, $ns_{hit}$, $is_{hit}$ and $a_{hit}$. Even if each of the four variables turns out to be non-stationary, equation (3.18) establishes that if there is convergence to a balanced growth path there must be a cointegration relation among those variables, i.e. a linear combination that is stationary.

## 4 The data

[10] Alternatively one could think of having a measure of R&D stock, as in Crepon and Duguet (1997). They estimate an analogous innovation function using a measure of R&D stock, built using the perpetual inventory method (see Hall and Mairesse, 1995). It can be shown that such measure can be expressed as a linear function of current R&D. This would clearly imply a different interpretation of the coefficient on R&D, which would then be a combination of the elasticity of new knowledge to R&D, the rate of growth and depreciation of R&D and, in our case, also the coefficient λ, which represents the portion of R&D of sector I employed in technology $i$ ($i \in$ I).

We use patent applications[11] at the European Patent Office (EPO) from six large, industrialized countries (France, Germany, Italy, Japan, UK and US) over the period 1981-1995[12]. These data come from the EP-CESPRI database, which includes all patent applications at the EPO from 1978, when the EPO was opened, up to 2004[13].

The data are classified into 135 technological fields, according to the classification provided by Grupp-Munt (1995). These technological fields, which represent our unit of analysis, are analogous to product groupings and belong to three major sectors: Chemicals (61 technological fields), Electronics (38 technological fields) and Machinery (36 technological fields)[14]. This classification allows us to perform the analysis at a finely defined level of aggregation in the countries where innovative activities are mostly performed and in the sectors where such activities are mostly important. For this reason, our sample appears well suited to study knowledge spillovers that takes place within sectors and across sectors, narrowly defined.

[Table 4.1 about here]

The distribution of patent applications by country and sectors in the sample is reported in Table 4.1. The countries included in the analysis account for over ninety percent of the patent applications at the EPO and each country share at the EPO is very similar to the share in our sample. Although limited to three sectors, this sample provides a good representation of the innovative activities by the above mentioned countries since about 68 percent of the patent applications from these countries belong to the chemicals, electronics and machinery sectors.

[Table 4.2 about here]

The EP-CESPRI database also includes the citations made by EPO patent

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[11] In what follows, whenever we refer to patents, we mean patent applications.
[12] Each patent is assigned to the country of residence of the applicant firm/institution.
[13] Individual applicants have been identified and excluded in the dataset used in the analysis. We also exclude the very first years of activity of the EPO because of the limited number of applications it received during those years.

applications to other EPO patents[15]. Table 4.2 shows the average number of national, international and self citations per patent in different sectors and countries[16]. The table shows that the number of citations to patents held by foreign firms or public institutions is consistently higher than that of citations to national patents, the gap being particularly wide in the UK, Italy and France. The only exception is the US, for which the weight of national citations (excluding self citations) is comparable to that of international citations.

The relative importance of international citations has been increasing in time while that of self citations has been steadily declining, as shown in Figure 4.1. The pattern shown in the figure is common to all European countries in the sample, with the gap between international citations, on one side, and national and self citations, on the other side, being particularly wide in Italy. This is partly due to a country size effect, but also confirms that Italy is strongly technologically dependent on foreign technology. By contrast, the gap between international citations and national citations is narrowing in time in Japan, while it is effectively null throughout the period in the US. This confirms the role of these two countries as technological leaders.

[Figure 4.1 about here]

Table 4.3 shows the percentage distribution of *national* citations. It is interesting to note that self-citations account for 45 percent of overall national citations in the whole sample and at least 50 percent in all countries, but Japan and the US. This might signal that innovative capacity is more diffused in the two technological leaders, compared to what happens in the remaining countries.

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[14] The distribution of the size of technological fields (i.e. the total number of applications over the whole sample period) is highly skewed, with the very large technological fields belonging to the electronics industry and to either Japan or the US.

[15] We have included in the sample also the citations to EPO patents passing through the World Intellectual Property Organization (WIPO).

[16] Note that in tracing and counting patent applications and citations we took co-patenting into account. Note, however, that co-patenting is not so widespread and quite equally distributed across sectors. The countries with the higher incidence of co-patenting are France (10 percent of patent applications are co-patents), the UK (9 percent) and Japan (7 percent). Co-patenting is instead particularly low in the US: only 3 percent of patent applications are the result of joint effort by more than one firm.

[Table 4.3 about here]

The last two columns of Table 4.3 also show that, although our technological fields might be thought as being narrowly defined, still over sixty percent of the citations are directed to other patents classified into the same technological field. The table clearly shows that this effect is quite important and it is invariant across countries, as the percentage is rather constant across countries. However it appears higher in electronics and machinery, compared to chemicals.

We use patent applications as our dependent variable and then use data on citations to build the spillover variables as explained in the previous section. R&D data are taken from the OECD-ANBERD database and are classified into 25 ISIC groupings. This involves a classification problem, since patents are classified according to the International Patent Classification (IPC), which is technology based and not easy to reconcile with product based classifications. In order to overcome this problem, we use the concordance between IPC and SITC Rev.2, provided by Grupp-Munt (1995) and combine it with the concordance between SITC Rev.2 and ISIC Rev.2, provided by the OECD[17], to assign each of the 135 technological fields to one of fifteen R&D groupings, reported in the Appendix (Table A.1).

## 5. Empirical results

### 5.1 Test of Unit Root

We suspect that variables on the right-hand side of equation (3.18) are non-stationary. We suspect also that shocks in the stock of knowledge and R&D should have a very persistent effect in the further generation of knowledge. Being aware that the limited number of observations of each single time series may generate a relevant lack of power in the tests, we provide a panel unit root test and apply recent panel cointegration techniques. We use the test proposed by Im et al. (2003) (IPS) which is

[17] This is available at the following website:
http://www.macalester.edu/research/economics/PAGE/HAVEMAN/Trade.Resources/TradeConcordances.html

the most powerful with short time series and can take into account a trend and serially correlated errors (see also Bottazzi and Peri 2007)[18]. Relaxing the restriction that the coefficient of the lagged dependent variable is homogeneous across all units of the panel, we suppose that the stochastic process $y_{it}$ is generated as follows:

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + v_{it} \tag{5.1}$$

IPS test the null hypothesis of unit roots $H_0$: $\beta_i=0$ for all *i* against the alternatives $H_1$: $\beta_i<0$, for $i=1,2,\ldots,N_1$, $\beta_i=0$, for $i=N_1+1,2,\ldots,N$. Under the alternative some of the individual time series may have unit roots. In the case of serial correlation IPS propose a separate Augmented Dickey Fueller (ADF) for each cross-section unit. As a result we estimate the following equation:

$$\Delta y_{it} = \alpha_i + \gamma_{it} t + \beta_i y_{i,t-1} + \sum_{j=1}^{p} \rho_{ij} \Delta y_{i,t-j} + v_{it} \tag{5.2}$$

We have a balanced panel with N=604 technological fields and T=14 (1982-1995). We include a constant and a trend and variables are demeaned to remove possible common time effect. IPS consider the following average statistics:

$$\overline{\tilde{t}}_{NT} = \frac{1}{N} \sum_{i=1}^{N} \tilde{t}_{iT}(p, \rho_i) \qquad \text{with } \rho_i = (\rho_{i1}, \rho_{i2}, \ldots, \rho_{ip})' \tag{5.3}$$

$\tilde{t}_{iT}$ is based on the standard ADF statistic of order *p* for unit *i*. IPS show that for T>5 and $N \to \infty$

[18] Levin et al. (2002), Maddala and Wu (1999) propose other tests for unit roots using panel data. However their asymptotic results depend on T going to infinity. IPS results, as shown below, depend on N going to infinity. We have also controlled our results using a method proposed by Bond et al. (2002). In particular they suggest to perform a simple F-test based on the OLS estimation of the following first-order autoregressive process: $y_{it} = \phi y_{i,t-1} + (1-\phi)u_i + v_{it}$. Results (not reported) shows that in all cases we cannot reject the null of a unit root.

$$\widetilde{Z} = \sqrt{N}\,\frac{\overline{\widetilde{t}}_{NT} - \mu}{\sigma} \Rightarrow N(0,1) \text{ where } \mu = E(\widetilde{t}_T) \text{ and } \sigma^2 = Var(\widetilde{t}_T) \tag{5.4}$$

[Table 5.1 about here]

Table 5.1 shows the values of the $\widetilde{Z}$ statistic and the p-values. For each test two different specifications are displayed with the order of autocorrelation $p$ equal to 2 and 4. We cannot reject the null of unit root at 95% significant levels for none of the variables in equation (3.18). Indeed, $rd_{hIt}$, $ns_{hit}$, $is_{hit}$ and $a_{hit}$ all appear to be I(1). Our supposition that shocks to national or international R&D and to the domestic stock of ideas have permanent effects is confirmed and the idea that they are I(1) processes is consistent with our interpretative framework.

We also test for the presence of a unit root in the variable $istra_{hit}$, which accounts for intra-sectoral international spillovers only, which we shall include in the regressions in next section, to show that international spillover effects are most likely to be intra-sectoral. Also for this variable we cannot reject the null of a unit root when we consider four periods to adjust for autocorrelation.

Finally we consider the first difference of the variable $a_{hit}$ and test for the unit root of $g^A_{hit}$. Differencing removes the trend and therefore the alternative hypothesis in this case is stationarity without a trend. Table 5.1 shows that we reject the null of unit root and $g^A_{hit}$ follows a I(0) process. Therefore $a_{hit}$ converges to a balanced growth path. These results suggest that there is a linear combination of $r_{hit}$, $ns_{hit}$, $is_{hit}$ and $a_{hit}$ that is stationary and, accordingly, we make use of cointegration analysis in order to estimate the cointegration vector.

### 5.2 The relevance of international spillovers

The unit root tests reported in the previous section confirmed our prior of non stationarity. We now proceed to analysing the long run behaviour between the stock of cumulated knowledge, R&D resources, national and international pools of knowledge, in order to verify whether they are linked by a cointegration relation. We now show that this is indeed the case. We first estimate the cointegration vector of equation (3.18) and then we test that the residuals of this regression are stationary.

We use dynamic ordinary least squares (DOLS) to estimate (3.18) on a panel of 604 technology-country pairs[19] and 15 years. We thus impose homogeneity on the cointegration vector across technological fields and countries, but allow for both fixed effects and time trends specific to technology-country pairs. We then partially weaken the homogeneity assumption, by estimating separate equations for the three main technological areas in our data, thus allowing for different cointegrating vectors in the chemicals, electronics, and machinery sectors.

The DOLS estimator is based on the following decomposition of the time varying error component to be added to equation (3.18):

$$\varepsilon_{hit} = \sum_{k=-\infty}^{+\infty} \gamma'_k \, \Delta x_{hi,t+k} + v_{hit} \tag{5.5}$$

where $\Delta x_{hit}$ includes the first-differences of all the I(1) regressors and $v_{hit}$ is orthogonal to all leads and lags of $\Delta x_{hit}$. This procedure corrects for the possible endogeneity of the non-stationary regressors and gives estimates of the cointegration vectors, which are asymptotically efficient when the error terms are independent across country-technology pairs. In practice, the infinite sums are truncated at some small numbers of leads and lags (see Breitung and Pesaran, 2005). The issue of how to choose different lags and leads in the panel cointegration is an interesting and difficult question, but it is not the focus of this paper. Furthermore, our time series includes only fifteen years, that is it is fairly short and including too many leads/lags would significantly affect our estimates. As a consequence, we insert (5.5) with only two lags into (3.18) and obtain the following cointegration relation:

[19] In order to exclude technological fields where innovation is a quite rare phenomenon, in each country, we exclude from the analysis those technological fields with less than 50 patent applications throughout the sample period.

$$
\begin{aligned}
\ln A_{hit} &= c_{hi} + \theta_{hi} t + \mu_1 r_{hIt} + \mu_2 ns_{hit} + \mu_3 is_{hit} + \\
&\quad + \sum_{k=-2}^{-1} \left( \gamma_{1k} \Delta r_{hI,t+k} + \gamma_{2k} \Delta ns_{hi,t+k} + \gamma_{3k} \Delta is_{hi,t+k} \right) + v_{hit}
\end{aligned} \tag{5.6}
$$

where $c_{hi}$ accounts for permanent differences in the innovation generating process of different country-technology pairs. As a robustness check, we then estimate the same equation including up to one lead of the differenced terms, as in Kao et al. (1999).

The estimates of the parameters $\mu_1$, $\mu_2$, $\mu_3$, are reported in Table 5.2, where we control for time trends by including heterogeneous (i.e. country-technology specific) time trends. For comparative purpose we also reports estimates with homogeneous time trend.

Our basic specification with heterogeneous time trends (column (2)) confirms that the long-run elasticities of knowledge creation to own R&D, and to national and international R&D are precisely estimated. An increase by 1% in own R&D resources is associated with a 0.12% increase in the domestically generated stock of scientific and technological knowledge. This is comparable to the increase generated by a 1% increase in the national pool of R&D resources coming from other technological fields ($\hat{\mu}_2$), which is equal to 0.13%. At the same time $\hat{\mu}_1$ is about half the increase originated by the same variation in the available international resources ($\hat{\mu}_3$=0.28), the difference being statistically significant.

[Table 5.2 about here]

As expected, the point estimate of the effect of own R&D is small when compared to analogous ones obtained in previous studies[20]. For instance Branstetter (2001) uses firm-level data and finds an elasticity of innovation to R&D equal to 0.72. Peri (2005), using data on sub-national regions, found values between 0.6 and 0.8. Because of the different level of aggregation of R&D compared to patent data, our

[20] See also Wieser, 2005 for a summary of the main estimates of output (sales, value added or TFP) elasticity of R&D at the firm level. He surveys 52 papers and shows that the median value of this elasticity is 0.13.

estimate of the elasticity of new knowledge to own R&D is reduced by λ, which is smaller than 1, by construction.

We find also that the elasticity of the stock of created knowledge to international spillovers is equal to 0.28. Also in this case the true value is smaller due to the presence of λ. However we can compare the estimated coefficients $\hat{\mu}_1$, $\hat{\mu}_2$ and $\hat{\mu}_3$ and we find that the ratios $\hat{\mu}_1$ to $\hat{\mu}_3$ and $\hat{\mu}_2$ to $\hat{\mu}_3$ are respectively 0.43 and 0.48. This implies a much higher effect of international sources of knowledge compared to what has been found in a similar setting by Bottazzi and Peri (2007). They find that the elasticity of domestically generated knowledge to international knowledge stock is about 55% the elasticity to own R&D. However, such estimates are obtained from country-level regression that do not distinguish between different technological fields, thus effectively including our pool of national external resources in the own R&D measure. Furthermore, this difference in the impact of international spillovers may depend upon a fundamental difference in how the spillover effect is measured. Bottazzi and Peri's measure of international knowledge stock is the simple summation of the stock of ideas generated in foreign countries, hence it is not weighted by the relevance and technological proximity of the source of knowledge to the destination. As a result we find that the spillover effect of *cited* international R&D on knowledge creation in a technological field is higher.

The second part of Table 5.2 reports results from the estimation of the cointegration relation adding two lags and one lead. These results are very similar to those obtained from adding just the two lags.

### 5.3 Intra-sectoral spillovers

In order to qualify our results, we substitute the variable representing the international spillover pool with the variable $istra_{hit}$, which accounts for intra-sectoral international spillovers only (Table 5.3).

[Table 5.3 about here]

The results are equivalent to those reported in Table 5.2. The elasticity of the stock of knowledge to the intra-sectoral component of international spillovers is almost identical to that of the knowledge stock to the complete international spillovers variable (*is*). This means that the effect of international spillovers is explained by its intra-sectoral component.

### 5.4 Differences across sectors

The point advanced in section 2 that there are differences across sectors in the importance of different types of spillovers is shown by assigning the 135 technological fields to the three sectors they belong to: electronics, chemicals and mechanicals.

Tables 5.4 and 5.5 show the results obtained from separate DOLS regressions on the three major sectors in our sample. In all regressions we included a country-technology specific time trend, according to our preferred specification.

[Tables 5.4 and 5.5 about here]

The effects of national and international spillovers differ across sectors. In the chemical sector the elasticity of new knowledge to national inter-sectoral external resources is comparable to that of own R&D at any level of significance, while the elasticity to international resources is at least twice larger. By contrast, in the electronics sector the effect of national and international spillovers is similar, and significantly larger (at the 1% level) than the effect of own R&D. Finally, in the machinery sector national inter-sectoral external resources do not appear to have any positive impact on new knowledge creation, while international sources of knowledge do contribute to new knowledge creation with an elasticity equal to that of own R&D.

Table 5.5 once again confirms that the intra-sectoral component in fact explains all the effect of international spillovers.

Therefore one could conclude that in chemicals knowledge flows are extremely sector-specific, given the very different sectoral context in which innovation takes place (biotechnology, new materials etc) and are also international. Electronics presents a similar feature, but with a relatively higher responsiveness of inter-sectoral spillovers, due to the convergence of electronics technologies and the inter-sectoral linkages that characterize the sector. Finally, in machinery the responsiveness of knowledge production to inter-sectoral spillovers is limited because knowledge is quite tacit and localized: knowledge is mainly sector specific and flows also internationally.

### 5.5 Test for cointegration

We need to check whether $a_{hit}$, $r_{hIt}$, $ns_{hit}$ and $is_{hit}$ ($istra_{hit}$) are indeed cointegrated. A test for cointegration is a test of stationarity of the residuals from regression (Tables 5.6 and 5.7). We perform seven different cointegration tests developed in Pedroni (1999). Four tests are based on pooling along the within dimension and the remaining three are obtained by pooling along the between dimension. The within-dimension based statistics are referred to as "panel" cointegration tests, while between-dimension based statistics are referred to as "group" cointegration tests. In all cases, the null hypothesis is that the first autoregressive coefficient of the residual series is equal to unity (i.e. no cointegration). All tests, after the appropriate standardisation, follow a standard normal distribution. In particular, Pedroni (1999) shows that under the alternative hypothesis (cointegration) the panel-variance statistics diverges to positive infinity, hence the right tail of the normal distribution is used to reject the null of no cointegration. By contrast, the other six statistics diverge to negative infinity under the alternative of cointegration, hence large negative values lead to rejection of the null of no cointegration. Five of the seven tests performed reject the null of no cointegration at the 1% significance level (Table 5.4). The two statistics failing to reject the null of no cointegration are the panel-rho and the group-rho statistics, which are undersized and tend to become overconservative in finite samples in which the N dimension exceeds the T dimension (Pedroni, 2004), as in our case.

[Tables 5.6 and 5.7 about here]

## 6. Final Remarks

Past conventional wisdom and recent firm level evidence has underlined that knowledge spillovers are mainly localized and occur within geographical boundaries. Recent macroeconomic empirical analyses have also shown that spillovers may be international in scope, using trade data to track knowledge flows.

The empirical methodology of this paper is based on a knowledge production function adapted to account for spillover effects and to solve the problem of different levels of sectoral aggregation between patents, citations and R&D data. We use patent citations and R&D to measure different types of spillovers: national and international, intra-sectoral and inter-sectoral ones. We provide a comparison of the relative importance of the different types of spillovers for a unique panel of 135 narrowly defined technological fields in chemicals, electronics and machinery in France, Germany, Italy, Japan, UK and US over the period 1981-1995. Our data set shows that citations to patents held by foreign firms are consistently higher than citations to national patents, and that their relative importance has been increasing in time. Moreover about sixty percent of the citations are directed to other patents classified into the same narrowly defined technological field.

This paper confirms the relevance of knowledge spillovers for innovative activity. It also confirms that international spillovers are very effective in fostering patenting activities, and finds that the spillover effect of cited international R&D on knowledge creation in a technological field is higher than previously considered.

To the existing literature this papers adds that these international spillovers mainly occur within narrowly defined knowledge domains, and therefore are intra-sectoral. This is because knowledge flows for innovation are highly sector and technology specific.

In addition, the paper shows that sectoral differences in the type of spillovers that are relevant for innovative activities exist and are significant. Patenting in chemicals is highly responsive to intra-sectoral international spillovers. Electronics has a relatively higher responsiveness to inter-sectoral spillovers. In machinery new knowledge is mainly sector specific and flows in a intra-sector and an international fashion.

# 7 Appendix

Table A.1 R&D data aggregation from the OECD/ANBERD database.

| ISIC REV. 2 | |
|---|---|
| 31 | Food, Beverages & Tobacco |
| 32 | Textiles, Apparel & Leather |
| 33 | Wood Products & Furniture |
| *34* | *Paper, Paper Products & Printing* |
| 35 | Chemical Products |
| 351+352-3522 | Chemicals excl. Drugs |
| 3522 | Drugs & Medicines |
| 353+354 | Petroleum Refineries & Products |
| 355+356 | Rubber & Plastic Products |
| 36 | Non-Metallic Mineral Products |
| 37 | Basic Metal Industries |
| 371 | Iron & Steel |
| 372 | Non-Ferrous Metals |
| 38 | Fabricated Metal Products |
| 381 | Metal Products |
| 382-3825 | Non-Electrical Machinery |
| 3825 | Office & Computing Machinery |
| 3830-3832 | Electric. Machin. excluding Commercial Equipment |
| 3832 | Radio, TV & Communication Equipment |
| 3841 | Shipbuilding & Repairing |
| 3843 | Motor vehicles |
| 3845 | Aircraft |
| 3842+3844+3849 | Other Transport Equipment |
| 385 | Professional Goods |
| 39 | Other Manufacturing |

The 135 technological fields employed in the analysis belong to the ISIC groupings whose rows have been evidenced. In only one case (one electronics technological field in the UK) we have used R&D data for "*Paper, Paper Products & Printing*".

Table A.2 Correlation matrix of the explanatory variables used in the regressions

| | ***logrd*** | ***ns*** | ***is*** |
|---|---|---|---|
| ***logrd*** | 1.0000 | | |
| ***ns*** | 0.1630 | 1.0000 | |
| ***is*** | 0.3232 | 0.0923 | 1.0000 |

Table A.3 List of technological fields

| **Chemicals** |
|---|
| Technical polymers; Thermoplastics; Polyacetale; Artificial and natural caoutchouc; Natural polymers; Plastic trash; Plastic products; Inorganic chemical compounds; Inorganic oxygen compounds; Inorganic sulphide compounds; Other metal salts; Other inorganic chemical products; Radioactive substances; Synthetic textile fibres; Artificial textile fibres; Trash; Organic oils and fats; Wax; Artificial wax; Chemical products of wood or resins; Hydrocarbons; Alcohol; Carbon acid; Compounds with nitrogen function; Organic-inorganic compounds; Lactam, other heterocyclic compounds; Sulphamide; Ether, alcohol peroxide; Synthetic organic colours and varnishes; Tanning agents and paint extracts; Colours, varnishes, pigments; Glazes, sealing compounds; Vitamins, provitamins, antibiotics; Hormones and derivatives; Micro-organisms, vaccines; Reagents and diagnostics; Other special medicines; Other pharmaceutical products; Cosmetics (no soaps) ; Etheric oils and perfumes; Soaps; Detergents; Ski-wax, furniture polishes; Fertilisers; Insecticides; Starch ; Proteins; Explosives, gunpowderv Fuses, ignition chemicals; Pyrotechnic articles, fireworks; Matches; Additives for lubricating oil, corrosion inhibitors; Liquids for hydraulic brakes, anti-freezing compounds; Lubricants, emulsions for grease, artificial graphite emulsion; Gas cleansing; Catalysts; Additives for metals; Benzol, naphtha; Electronic and electro-technical chemical compounds; Chemical substances for constructions; Chemicals for fire extinguishers, liquid polychlor diphenyle; |
| **Electronics** |
| Ignition cables, electrical cars; Small electrical engines, electrodes; Portable electrical tools; Motors, electrical engines and electrodes; Magnetic tapes; Choke coils, converters, transformers; Traffic lights, etc.; Generators and equipment; Particles accelerator; Transformers; Lasers; Fridges (for home and industry), air conditioning; Washing machines, dryers, dish washers; Electrical shavers, hair-cutting machines, hoovers; Electric heating; Computers and equipments; Computer chips and equipments; Photocopying machines and equipments; Type-writers and other office devices; TV, radio, TV-cameras, video-cameras, antennas, oscilloscopes; Microphones, loud-speakers, recorders; Telephones (no mobile phones); Radio engineering devices; Circuits; Resistors; Switches, fuses; Control panels; Cables (without ignition); Insulators; Capacitors; Electro-magnets; Electrical diagnostic devices (no X-rays); X-rays; Instruments to show ionic beams; Diodes, transistors; Integrated circuits; Batteries, accumulators; Portable electrical lamps |
| **Machinery** |
| Printing machines; Steam-boiler; Machines for food processing; Steam-turbines for ships; Steam-turbines for steam power plants; Machines to process rocks, etc.; Gas-turbines for aeroplanes; Gas-turbines for power stations; Wood processing machines; Plastic processing; Cutting machine tools (saws, etc.); Non cutting machine tools; Metal-working rolling mills; Soldering irons, blow lamps, welders; Torches, furnaces; Ovens, distilling apparatuses, gas distilling; Piston-drive engines for aeroplanes ; Pumps, centrifuges, filters; Engines for cars; Conveyors; Engines for ships; Anti-friction bearing; Engines for trains; Valves; Packaging machines; Scales; Fire extinguisher, spray guns; Other machines; Water-turbines; Nuclear power reactors; Other engines; Agricultural machines (without tractors); Tractors; Constructions and mining machines; Textile machines; Paper production machines |

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## Tables and Figures

Table 4.1 Number and distribution of patent applications in the sample by country and sector

| **Country of applicant** | **Number of patents** | **% share** |
|---|---|---|
| *Germany* | 89279 | 22 |
| *France* | 33095 | 8 |
| *UK* | 28729 | 7 |
| *Italy* | 15043 | 4 |
| *Japan* | 94641 | 24 |
| *US* | 139816 | 35 |
| Total | 400603 | 100 |

| **Sector** | **Number of patents** | **% share** |
|---|---|---|
| *Chemicals* | 132434 | 33 |
| *Electronics* | 163681 | 41 |
| *Machinery* | 104488 | 26 |
| Total | 400603 | 100 |

Table 4.2 Average number of citations per patent by type

| **Country**(*) | | **Citations** | |
|---|---|---|---|
| | **Self** | **National**(**) | **International** |
| *Germany* | 0,23 | 0,19 | 0,40 |
| *France* | 0,16 | 0,14 | 0,54 |
| *UK* | 0,23 | 0,18 | 0,58 |
| *Italy* | 0,16 | 0,13 | 0,55 |
| *Japan* | 0,25 | 0,33 | 0,41 |
| *US* | 0,23 | 0,33 | 0,34 |
| *All* | 0,23 | 0,27 | 0,41 |
| **Sector**(*) | | **Citations** | |
| | **Self** | **National**(**) | **International** |
| *Chemicals* | 0,37 | 0,33 | 0,52 |
| *Electronics* | 0,17 | 0,28 | 0,40 |
| *Machinery* | 0,13 | 0,16 | 0,27 |
| *All* | 0,23 | 0,27 | 0,41 |

(*) Country and Sector refer to the citing patent.
(**) National citations are citations to national firms, universities and public research centers and exclude self citations, which are reported in the last column.

Table 4.3 Percentage distribution of national citations

| Country(*) | Self | Others | Intra-field | Inter-field |
|---|---|---|---|---|
| *Germany* | 0,55 | 0,45 | 0,66 | 0,34 |
| *France* | 0,50 | 0,50 | 0,68 | 0,32 |
| *UK* | 0,53 | 0,47 | 0,62 | 0,38 |
| *Italy* | 0,54 | 0,46 | 0,66 | 0,34 |
| *Japan* | 0,43 | 0,57 | 0,65 | 0,35 |
| *US* | 0,39 | 0,61 | 0,66 | 0,34 |
| *All* | 0,45 | 0,55 | 0,66 | 0,34 |
| **Sector(*)** | **Self** | **Others** | **Intra-field** | **Inter-field** |
| *Chemicals* | 0,52 | 0,48 | 0,59 | 0,41 |
| *Electronics* | 0,37 | 0,63 | 0,72 | 0,28 |
| *Machinery* | 0,45 | 0,55 | 0,70 | 0,30 |
| *All* | 0,45 | 0,55 | 0,66 | 0,34 |

The first two columns give the percentage distribution of national patents distinguishing between self citations and citations to patents held by other national firms, national universities and public research centers. The last two columns refer to the distribution of citations to patents held by other national firms between cited patents classified in the same technological field (intra-field) vs. a different technological field (inter-field).

(*) Country and Sector refer to the citing patent.

Figure 4.1. The evolution of the relative share of citations by type.

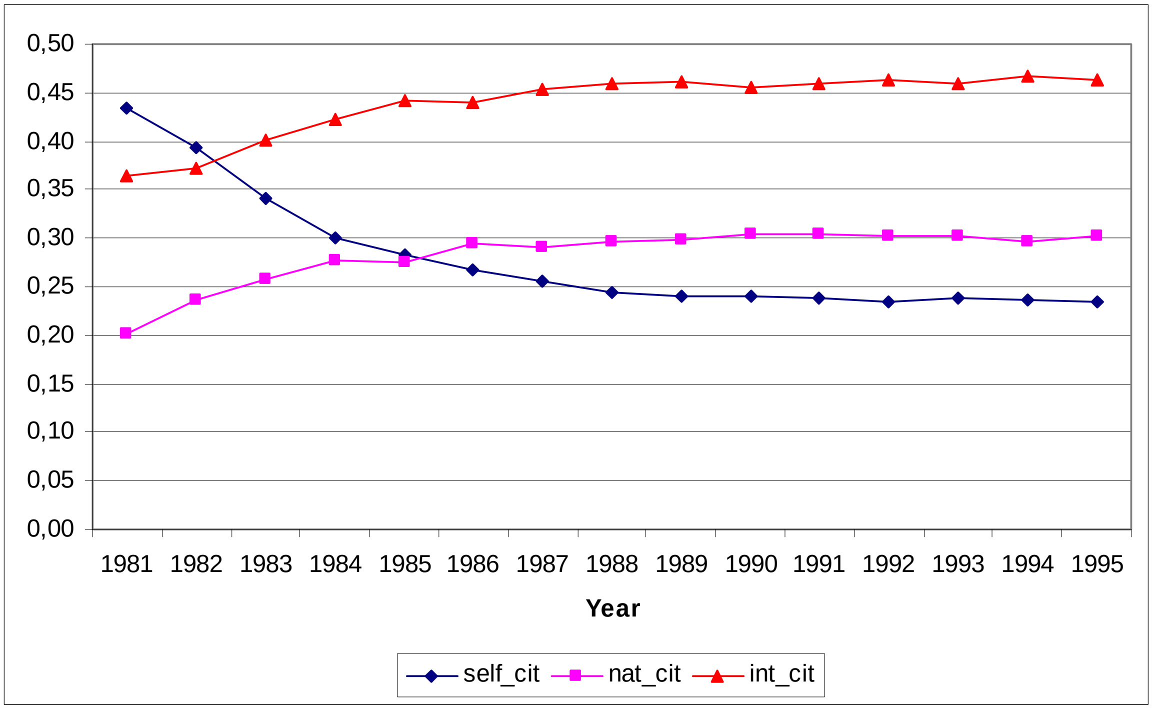

Table 4.1 Test of Unit Roots

| | Variables | *a* | *rd* | *ns* | *is* | *istra* | *Δa* |
|---|---|---|---|---|---|---|---|
| ADF(2) | Statistic $\widetilde{Z}$ | -1.34 | 0.64 | 0.19 | 5.16 | **-3.570** | **-14.35** |
| | p-value | 0.09 | 0.74 | 0.58 | 1.00 | **0.000** | **0.00** |
| ADF(4) | Statistic $\widetilde{Z}$ | 2.249 | 1.89 | 3.06 | 8.36 | 0.498 | **-4.95** |
| | p-value | 0.99 | 0.97 | 0.99 | 1.00 | 0.691 | **0.00** |
| Trend | | Yes | Yes | Yes | Yes | Yes | No |
| Constant | | Yes | Yes | Yes | Yes | Yes | Yes |

Note. Bold characters denote rejection of the null of a unit root at the 5% level.

Table 5.2. Estimates of the long-run cointegration relationship with DOLS on the complete sample

| | *DOLS with two lags* | | *DOLS with two lags - one lead* | |
|---|---|---|---|---|
| *Dependent variable: a* | (1) | (2) | (3) | (4) |
| *rd* | 0.15 | 0.12 | 0.21 | 0.19 |
| | (0.02) | (0.01) | (0.02) | (0.02) |
| *ns* | 0.11 | 0.13 | 0.16 | 0.20 |
| | (0.05) | (0.03) | (0.06) | (0.04) |
| *is* | 0.10 | 0.28 | 0.14 | 0.33 |
| | (0.04) | (0.02) | (0.05) | (0.03) |
| Heterogeneous time trend | No | Yes | No | Yes |
| Observations | 7248 | 7248 | 6644 | 6644 |

Note. Robust standard errors in parethesis.
(1) and (3): Homogeneous trend; (2) and (4): Heterogeneous trend;

Table 5.3. Estimates of the long-run cointegration relationship with DOLS on the complete sample

| | *DOLS with two lags* | | *DOLS with two lags - one lead* | |
|---|---|---|---|---|
| *Dependent variable: a* | (1) | (2) | (3) | (4) |
| *rd* | 0.14 | 0.12 | 0.20 | 0.19 |
| | (0.02) | (0.01) | (0.02) | (0.02) |
| *ns* | 0.15 | 0.18 | 0.21 | 0.26 |
| | (0.05) | (0.03) | (0.06) | (0.04) |
| *istra* | 0.13 | 0.32 | 0.13 | 0.37 |
| | (0.04) | (0.03) | (0.06) | (0.04) |
| Heterogeneous time trend | No | Yes | No | Yes |
| Observations | 7248 | 7248 | 6644 | 6644 |

Note. Robust standard errors in parethesis.
(1) and (3): Homogeneous trend; (2) and (4): Heterogeneous trend;

Table 5.4. Estimates of the long-run cointegration relationship with DOLS for three sectors

| | *DOLS with two lags* | | | *DOLS with two lags - one lead* | | |
|---|---|---|---|---|---|---|
| *Dependent variable: a* | *Chemicals* | *Electronics* | *Machinery* | *Chemicals* | *Electronics* | *Machinery* |
| *rd* | 0.14 | 0.08 | 0.14 | 0.28 | 0.12 | 0.22 |
| | (0.04) | (0.02) | (0.02) | (0.06) | (0.03) | (0.02) |
| *ns* | 0.15 | 0.12 | 0.04 | 0.21 | 0.23 | 0.05 |
| | (0.06) | (0.05) | (0.04) | (0.09) | (0.07) | (0.06) |
| *is* | 0.48 | 0.17 | 0.12 | 0.46 | 0.22 | 0.16 |
| | (0.04) | (0.03) | (0.03) | (0.06) | (0.04) | (0.04) |
| Heterogeneous time trend | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2652 | 2340 | 2256 | 2431 | 2145 | 2068 |

Note. Robust standard errors in parethesis.

Table 5.5. Estimates of the long-run cointegration relationship with DOLS for three sectors

| | *DOLS with two lags* | | | *DOLS with two lags - one lead* | | |
|---|---|---|---|---|---|---|
| *Dependent variable: a* | *Chemicals* | *Electronics* | *Machinery* | *Chemicals* | *Electronics* | *Machinery* |
| *rd* | 0.17 | 0.08 | 0.13 | 0.34 | 0.11 | 0.22 |
| | (0.04) | (0.02) | (0.01) | (0.06) | (0.03) | (0.02) |
| *ns* | 0.19 | 0.16 | 0.07 | 0.24 | 0.29 | 0.11 |
| | (0.06) | (0.05) | (0.04) | (0.09) | (0.07) | (0.06) |
| *istra* | 0.65 | 0.18 | 0.14 | 0.53 | 0.22 | 0.17 |
| | (0.07) | (0.04) | (0.04) | (0.09) | (0.05) | (0.06) |
| Heterogeneous time trend | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2652 | 2340 | 2256 | 2431 | 2145 | 2068 |

Note. Robust standard errors in parethesis.

Table 5.6 Test of cointegration – regression with *is*

| | *All sample* | *Chemicals* | *Electronics* | *Machinery* |
|---|---|---|---|---|
| panel v-stat | **25.83** | **18.03** | **30.92** | **31.59** |
| panel rho-stat | 16.48 | 16.42 | 16.96 | 16.57 |
| panel pp-stat | **-12.67** | **-14.56** | **-10.90** | **-12.19** |
| panel adf-stat | **-11.53** | **-10.90** | **-11.48** | **-12.01** |
| group rho-stat | 25.50 | 25.12 | 25.93 | 25.52 |
| group pp-stat | **-14.24** | **-17.16** | **-13.56** | **-14.96** |
| group adf-stat | **-16.53** | **-16.03** | **-18.91** | **-18.63** |

Note. All reported values are distributed N(0,1) under null of unit root or no cointegration
Bold characters denote rejection of the null of unit root (no cointegration) at the 1% level.

Table 5.7 Test of cointegration – regression with *istra*

| | *All sample* | *Chemicals* | *Electronics* | *Machinery* |
|---|---|---|---|---|
| panel v-stat | **8.64** | **9.21** | **9.33** | **9.37** |
| panel rho-stat | 7.32 | 7.23 | 7.26 | 6.64 |
| panel pp-stat | **-13.37** | **-12.81** | **-12.32** | **-14.57** |
| panel adf-stat | **-14.17** | **-13.24** | **-14.52** | **-14.78** |
| group rho-stat | 17.64 | 17.57 | 17.49 | 16.89 |
| group pp-stat | **-15.83** | **-14.73** | **-14.50** | **-17.56** |
| group adf-stat | **-19.91** | **-18.62** | **-20.13** | **-21.60** |

Note. All reported values are distributed N(0,1) under null of unit root or no cointegration
Bold characters denote rejection of the null of unit root (no cointegration) at the 1% level.