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

Franco Malerba[∇], Maria Luisa Mancusi^{*} Fabio Montobbio⁺

Abstract

We analyze the relative effects of national and international, intra-sectoral and inter-sectoral R&D spillovers on innovative activity in six large, industrialized countries over the period 1980-2000. 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. Using panel cointegration we show that inter-sectoral spillovers have a key impact on innovation activities and that domestic R&D has a stronger effect than international R&D. However, within technological fields, estimated international R&D spillovers are 2.4 times the national R&D effects. We find significant differences across chemicals, electronics and machinery industries.

JEL Codes: F0, O3, R1

Keywords: R&D spillovers, Knowledge flows, Patent citations, Panel cointegration.

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1 Introduction

In the past two decades macroeconomic models have underlined the importance of knowledge spillovers and described how they increase innovative activity and productivity (e.g. Rivera-Batiz and Romer, 1991; Grossman and Helpman, 1991). As a consequence a number of empirical contributions have employed different methodologies and techniques to measure different types of spillovers at different aggregation levels.

This paper adds to the exiting literature by comparing in a unified framework national and international, intra-sectoral and intersectoral knowledge spillovers. In addition we examine the sectoral heterogeneity of these spillovers. There are few works on international R&D spillovers that focus on spillovers across sectors (e.g. Keller, 2002; Frantzen, 2002; Park, 2004; Mancusi, 2008). However these studies work at a very high level of aggregation and most often 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 industries (chemicals, electronics and machinery) to measure and compare different types of R&D spillovers: within field vs. across fields, and national vs. international¹.

Using a knowledge production function we develop an empirical model to estimate the different types of spillovers in a unified framework using panel cointegration. 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 1980-2000. Patent applications serve as a measure of innovative output, while their citations are used to account for patent quality and to measure the direction and intensity of knowledge flows within and across technological fields and national boundaries.

Our results show that sectoral R&D affects importantly innovation activities and that the distinction between inter-sectoral and intra-sectoral spillovers is strong and significant. In addition, we show that national R&D effects are stronger than international ones, but when the distinction between intra-sectoral and inter-sectoral spillovers is made, the estimated international spillovers effects within narrowly defined technological fields are more than twice the national ones. Thus it is possible to claim that inter-sectoral knowledge flows are much more constrained by geographical distance (and in particular national borders) than intra-

¹ We use the word *industry* to refer to broad aggregates like chemicals, electronics and machinery. Our unit of analysis is much more detailed and very close to product groups. We refer to these groups (listed in the Appendix) as *technological fields or technological sectors*. We use the term *class* to refer to specific classifications (like IPC for patents, SITC for trade data or ISIC).

sectoral ones, which diffuse globally. Finally we show that there are important differences across industries. In chemicals inter-sectoral spillover (both national and international) effects have a much larger magnitude than in electronics, where only international intra-fields spillovers are statistically significant.

Our analysis has major policy implications. First of all it affects the perspective on optimal R&D and technology policy of a country. Countries that are more open and able to learn can innovate substantially faster, but learning, in particular across geographical and technological boundaries, can be costly. It is therefore very important to understand how this process occurs in different industries. In addition our question has important implications for the effectiveness of R&D policy because the impact of R&D subsidies may follow industry-specific trajectories that are affected by geography and by the input-output structure of the innovation process.

The paper is organized as follows. Section 2 discusses the existing evidence on knowledge spillovers at the macro and micro level, provides the motivation for our analysis and sketches the main hypotheses. In Section 3 we present the empirical model that illustrates the relationship between innovation and the different types of spillovers. Section 4 describes the data and provides some descriptive evidence. In Section 5 we report and discuss the results from the econometric analysis. In Section 6 we draw our conclusions.

2. Knowledge production and spillovers

Theoretical work on endogenous technical change has provided a framework to understand knowledge spillovers. Technology is typically considered as non-rival and R&D investments have both private and public returns. R&D expenditures therefore create new knowledge and technology can be used - locally or internationally - within the same industry and - locally and internationally - in different industries. These external effects are not automatic as they require domestic investments in technology absorption (Cohen and Levinthal, 1989; Griffith et al. 2004). Knowledge may be codified in publicly available sources, such as scientific and technical literature, or may also be transferred through industrial espionage or reverse engineering. It may be simply absorbed and used to imitate (*imitation-enhancing spillovers*) (Los and Verspagen 2003) or, most importantly, it may stimulate new ideas which in turn lead to innovations (*idea-creating spillovers*).

Innovation activity can also benefit from these external effects via tangible and

intangible inputs. The literature has identified additional important channels of technology diffusion: international trade, foreign direct investment (FDI) and mobility of human capital. Importing intermediate goods and final products is an important vehicle of knowledge transmission together with Foreign Direct Investments (FDI) via the physical presence of affiliate plants and mobility of skilled human capital (Keller and Yeaple, 2009; Gorg and Greenaway 2001).

[Table 2.1 about here]

This paper estimates and compares in a unified framework four types of spillovers: intra-national and intra-sectoral, intra-national and inter-sectoral, inter-national and intra-sectoral, inter-national and inter-sectoral. For simplicity we refer to these types of spillovers as A, B, C and D, according to the matrix presented in Table 2.1. Despite the very large number of papers, theoretical and empirical studies do not identify a precise ranking between these different types of spillovers. Estimates vary widely and it is difficult to consistently compare the relative impact of these different types of spillovers. Furthermore, few empirical studies account for both the international and the sectoral dimension and, even if they do, they typically employ highly aggregated industries and therefore cannot fully account for sectoral specificities in knowledge transmission.

In what follows, we shall first use the existing literature to identify some hypotheses on the relative importance of A, B, C and D.

2.1 Does geography and national borders constrain knowledge diffusion?

Technological diffusion is shaped by geography because there are communication and learning costs. These costs not only depend on geographical distance but are also affected by cultural barriers (like language). Barriers to the diffusion of knowledge exist because at least part of the knowledge is tacit and tacit knowledge is costly to codify, difficult to absorb and is mainly transmitted person to person (Keller 2002; 2004, 2010; Breschi and Lissoni, 2001)². So we expect that

a. national knowledge spillovers are, ceteris paribus, stronger than international

² Many papers show that knowledge spillovers tend to be geographically localized (e.g Maruseth and Verspagen 2002; Bottazzi and Peri, 2003; Peri, 2005; Branstetter, 2001)

knowledge spillovers

In terms of the different types of spillovers displayed in Table 2.1, we should then expect $A > C$ and $B > D$. In addition there is substantial evidence that knowledge flows cross also national borders³. There is also a great number of articles that measure the impact of trade related international R&D spillovers on total factor productivity (TFP)⁴. With few exceptions these papers support the idea that trade related international spillovers affect TFP. In addition FDI and labour mobility are other important channels that may decrease the communication and transport costs and favour the international dissemination of knowledge (Keller and Yeaple, 2009; Owen-Smith and Powell, 2004; Stephan, 1996; Montobbio and Sterzi, 2011).

b. The importance of international knowledge spillovers (vis à vis national spillovers) depends upon the degree of tacitness and how transmission channels affect communication and transport costs.

In particular in industries where international trade, FDI and labour mobility are important and demand is global, the cost of knowledge communication may be low, particularly so when the source and the destination of the flows share the same knowledge base. Hence, C would not necessarily be smaller than A, and could be even larger (also depending on the distance from the technological frontier). This brings us to a further relevant issue.

2.1. Does technological distance constrains the diffusion of knowledge?

Knowledge spillovers depend upon technological distance because it is less costly to learn from the same technology and technological opportunities develop along specific trajectories (Atkinson and Stiglitz, 1969; Rosenberg, 1976; Dosi, 1988). Most of the times, technical change takes place in the proximity of the current techniques, through learning by doing (Arrow, 1962) and incremental search (Malerba, 1992). So the current set of techniques

³ See for example Bottazzi and Peri (2007) and Mancusi, (2008). Further evidence on international knowledge flows is in Jaffe and Trajtenberg (1999) and Bacchiocchi and Montobbio (2010).

⁴ For example Coe and Helpman (1995), Eaton and Kortum (1996), Keller (1998), Frantzen (2002), Park (2004) and Keller (2010). Some doubts are cast by Kao et al. (1999) and Edmond (2001) that use panel cointegration econometrics and by Luintel and Kahn (2004) that suggest that data from different countries cannot be pooled.

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.

At the same time technological knowledge diffuses also across industry boundaries because the production of new ideas, products and processes use (knowledge) inputs that come from other fields. Spillovers are embedded in intermediate inputs and are generated through trade. At the same time many authors show also that there are specific connections among technologies (in their use and production) that do not depend necessarily upon tradable inputs (Scherer, 1984; and Evenson et al. 1991; Mohnen, 1997; Verspagen, 1997; Malerba and Montobbio, 2003; Bernstein 1988 and Bernstein and Nadiri 1988). As a result the degree to which industries benefit from inter-sectoral spillovers depend upon how much their knowledge base depends upon knowledge from other fields.

c. We should expect higher inter-industry spillovers in downstream sectors, if the variety of intermediate inputs is high and technological distance is low

As a result the relative size of A vs. B and C vs. D is mainly an empirical question. Keller (2002) estimates international and inter-sectoral R&D spillovers on TFP and finds $A > B$. His comparison between C and D is less univocal and results change according to the way inter-sectoral spillovers are calculated. Wieser (2005) summarizes a broad set of heterogeneous contributions 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 because different studies measure spillovers in different ways and use different econometric strategies.

2.3 Why may the geographical reach of (intra-industry and inter-industry) knowledge spillovers differ across industries?

The geographical reach of knowledge spillovers can be affected by the technological distance between the sender and the receiver. Geographical distance and technological distance can be considered to approximate two different communication and learning costs. Inventors and companies are better able to recognize and absorb knowledge that is similar to their

knowledge base: in this case, communication costs are lower. So we expect that intra-sectoral knowledge flows are much less affected by distance than the inter-sectoral ones. By contrast, if the innovating firm needs knowledge and technological inputs that are different from (possibly complementary to) its knowledge base, international spillovers may be more costly to extract. National borders matter because within these borders it is easier for innovators to identify, communicate and absorb those spillovers that come from knowledge that is distant in terms of knowledge base.

d. We expect the size of the inter-sectoral R&D spillover to be affected by geographical distance more than intra-sectoral spillovers. However, this effect may vary across-industries.

Results may vary across industries because technologies vary in the extent to which they use knowledge coming from other fields. Tangible and intangible inputs not only come from different sectors but are absorbed and applied under sector-specific transfer costs.

With reference to the three sectors examined in this paper, we claim that electronics is a highly globalized sector, with extensive multinational corporations and broad sectoral boundaries ranging from computers, to software, to telecom to consumer electronics. Therefore one may think that in electronics knowledge flows have a major international dimension through the activities of multinational corporations, offshoring and the international mobility of skilled personnel (Mowery, 1996). So in this case it is possible to observe $C > A$. The machinery sector, on the other hand, has major vertical links with industrial users taking place in local clusters: one therefore one may think that there is an intersectoral component of knowledge flows and that this intersectoral dimension is local and not international (Wengel and Shapira, 2004). So in this case we expect $A > C$ and $B > D$. Finally, chemicals have a less global dimension than electronics, and cross-country mobility of skilled personnel is less pronounced. For example we will show that in the chemical industry there is a greater share of knowledge acquired from other fields and therefore we not only expect to find stronger inter-industry spillovers but also a higher importance of geographical proximity (Arora et al. 2000). As a result in the chemical industry we might expect $B > A$ and $A > C$.

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:

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

where Q_{hit} is some latent measure of technological output in technological field i ($i = 1, \dots, 135$), country h and period t , R_{hit} measures the corresponding R&D investment, α represents the unknown technology parameter and v_{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:

$$Q_{hit} = \tilde{R}_{hit}^{\alpha} v_{hi} \quad (3.2)$$

$$\tilde{R}_{hit}^{\alpha} = R_{hit}^{\alpha_1} \cdot NS_{hit}^{\alpha_2} \cdot IS_{hit}^{\alpha_3} \cdot A_{hit}^{\alpha_4} \quad (3.3)$$

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:

$$P_{hit} = Q_{hit} e^{\theta_{hit}} u_{hi} \quad (3.4)$$

with $e^{\theta_{hit}}$ 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:

$$P_{hit} = \tilde{R}_{hit}^{\alpha} e^{\theta_{hit}} \xi_{hi} \quad (3.5)$$

We cannot directly estimate (3.5) because we do not have the same level of sectoral aggregation for R&D and patent and citation data. Indeed, as we shall explain in section 4, we use the OECD-ANBERD R&D data of manufacturing ISIC classes, while we re-aggregate patents and patent citations into 135 technological fields. We account for this data limitation in our model and make the following assumption:

$$R_{hit} = R_{hit}^{\lambda} \zeta_{hi} \quad \text{where } i \in I \quad (3.6)$$

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, ζ_{hi} . Using (3.3) and (3.6), equation (3.5) then becomes:

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

We trace knowledge flows using patent citations. National spillovers are measured as:

$$NS_{hit} = \prod_{j \neq i} S_{hjt}^{nc_{hij}} \quad (3.8)$$

S_{hjt} measures R&D stock at period t , accumulated from past R&D investments in industry j , country h and is calculated from own R&D investment during the previous period (R_{hjt-1}) using the perpetual inventory method (Hall and Mairesse, 1995)⁵. nc_{hij} is the relative number of citations over the whole sample period from patents classified into technological field i to patents classified into technological field j and held by other firms in the same country h ⁶.

International spillovers are measured in a similar manner as:

$$IS_{hit} = \prod_{j,f} S_{fjt}^{ic_{hij}} \quad (3.9)$$

where ic_{hij} is the relative number of citations, again over the whole sample period, from patents held by firms in country h and classified into technological field i to patents held by firms in country f and classified into technological field j .

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

$$A_{hi,t+1} = P_{hit} + (1 - \delta)A_{hit} \quad (3.10)$$

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:

$$A_{hi1981} = \frac{P_{hi1981}}{(\bar{g}_{hi} + \delta)} \quad (3.11)$$

⁵ This is calculated as $S_{hjt} = (1 - \delta)S_{hjt-1} + R_{hjt-1}$ using a depreciation rate (δ) of 15 percent (Hall and Mairesse, 1995). The first period stock is thus obtained as $S_{hj1} = R_{hj1} / (\delta + g_{hj})$, where g_{hj} is the growth rate of R&D spending in industry j , country h . This is industry-country specific and calculated as the average growth rate over the available period.

⁶ 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 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 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.

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

$$\ln P_{hit} = \lambda\alpha_1 r_{hit} + \lambda\alpha_2 ns_{hit} + \lambda\alpha_3 is_{hit} + \alpha_4 a_{hit} + \theta_{hi}t + \omega_{hi} \quad (3.12)$$

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

$$ns_{hit} = \sum_{j \neq i} nc_{hij} \ln R_{hjt} \quad (3.13)$$

$$is_{hit} = \sum_j ic_{hij} \sum_{f \neq h} rc_{hf} \ln R_{fjt} \quad (3.14)$$

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 over the entire sample period.

The international spillover variable in (3.14) includes both intra-sectoral (within technological field⁷) spillovers and inter-sectoral (between technological fields) spillovers. In particular, the first component is equal to:

$$istra_{hit} = ic_{hii} \sum_{f \neq h} rc_{hf} \ln R_{fjt} \quad (3.15)$$

Note that, as in Branstetter (2001) we have only current R&D in the patent equation. This is because distributed lags on R&D induce a multicollinearity problem in the estimation, as noted by Hall et al. (1986). Furthermore, our equation includes a measure of knowledge stock accumulated within the field-country (a_{hit}).

Dividing equation (3.10) by A_{hit} and re-arranging we obtain:

$$\frac{P_{hit}}{A_{hit}} = g_{hit}^A + \delta \quad (3.16)$$

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 (3.12) into (3.16) we obtain:

$$\ln(g_{hit}^A + \delta) = \lambda\alpha_1 r_{hit} + \lambda\alpha_2 ns_{hit} + \lambda\alpha_3 is_{hit} + (\alpha_4 - 1)a_{hit} + \theta_{hi}t + \omega_{hi} \quad (3.17)$$

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

⁷ See footnote 1 for the use of the terms *sectors* and *fields*.

stationary stochastic process. Equation (3.17) then represents the long-run relationship between r_{hit} , ns_{hit} , is_{hit} and a_{hit} . Even if each of the four variables turns out to be non-stationary, equation (3.17) 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. The cointegration vector, standardizing by the coefficient of a_{hit} , would be $\left(-1, \mu_1 = \frac{\lambda\alpha_1}{1-\alpha_4}, \mu_2 = \frac{\lambda\alpha_2}{1-\alpha_4}, \mu_3 = \frac{\lambda\alpha_3}{1-\alpha_4}\right)$ and can be estimated using the following equation:

$$a_{hit} = \mu_1 r_{hit} + \mu_2 ns_{hit} + \mu_3 is_{hit} + \theta_{hi} t + c_{hi} \quad (3.18)$$

where all the deterministic stationary variables are included in c_{hi} .

4 The data

We use patent applications⁸ at the EPO from six large, industrialized countries (France, Germany, Italy, Japan, UK and US)⁹. These data come from the EP-KITeS database, which includes all patent applications at the EPO (including those going through the Patent Cooperation Treaty) published by 2007¹⁰. However, due to a variable time lag between a patent application and its publication, we need to exclude the last years of the series as not all patent applications in those years are published by 2007 (hence included in the EP-KITeS database). The average time lag between application and publication is 18 months, so it is safe to exclude from the analysis the last three years of data. Furthermore, we shall build our knowledge stock variable weighting patent applications by the number of citations received within 4 years from application. This is a common procedure in the literature that allows accounting for patent quality and therefore implies that we can consider patent applications through to 2000. Finally, we also exclude the very first years of activity of the EPO because of the limited number of applications it received during those years: our available sample hence ranges from 1980 to 2000.

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 industries: Chemicals (61 technological fields), Electronics (38 technological fields) and Machinery (36

⁸ In what follows, whenever we refer to patents, we mean patent applications.

⁹ Each patent is assigned to the country of residence of the inventor.

¹⁰ Individual applicants have been identified and excluded in the dataset used in the analysis.

technological fields)¹¹. 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 industries where such activities are mostly important. For this reason, our sample is well suited to study knowledge spillovers taking place within and across narrowly defined sectors.

[Table 4.1 about here]

The distribution of patent applications by country and industries 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 industries, 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 industries.

[Table 4.2 about here]

The EP-KITeS database also includes the citations made by EPO patent applications to other EPO patents¹². 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; Mancusi, 2008). Citations are used by examiners and applicants to show the degree of novelty and inventive step of the claims of the patent. They are introduced 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)¹³.

¹¹ The list of fields is reported in Table A.2. 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.

¹² We have included in the sample also the citations to EPO patents passing through the World Intellectual Property Organization (WIPO).

¹³ 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 by the Community Innovation Survey data for the EPO

We use patents and patent citations from the EPO, which are, with few exceptions, added by the patent office examiners (EPO, 2005; Breschi and Lissoni, 2004)¹⁴ when they draft their search report¹⁵. This reduces the probability to have citations that are erroneously or strategically included to deceive patent examiners.

Table 4.2 shows the average number of national, international and self citations (these are within-firm citations i.e. citations to a patent with the same applicant) per patent in different industries and countries¹⁶. 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 higher than 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. Analogous figures for the single countries are not reported to save space¹⁷, since they show a pattern similar to that of Figure 4.1. It is however interesting to notice that the gap between international citations, on one side, and national and self citations, on the other side, is particularly wide in Italy. This is partly due to a country size effect, but also suggests that Italy is technologically dependent on foreign technology. By contrast, the gap between international citations and national citations is narrowing in time in Japan, while in the US the share of national citations is higher than the share of international citations. This confirms the role of these two countries as technological leaders.

(Duguet and MacGarvie 2005) and corroborates substantial evidence on the type and nature of knowledge spillovers (e.g. Maruseth and Verspagen, 2002; Jaffe et al. 1993, Bacchiocchi and Montobbio, 2010).

¹⁴ 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.

¹⁵ 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.

¹⁶ National citations and international citations are citations to patents held by firms resident respectively in the same and in a different country. Self citations are citations to previous patents held by the same applicant firm. 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 industries. 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.

¹⁷ These are obviously available upon request.

[Table 4.3 about here]

Table 4.3 shows the percentage distribution of *national* and *international* citations. It is interesting to note that self-citations account for 36 percent of overall national citations in the whole sample, for over 50 percent in Italy and France and 40 percent in all countries, but the US. This signals that innovative capacity is more diffused in the US, compared to the remaining countries. In both the national citations and international citations sections of the Table 4.3, the last two columns 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, it is invariant across countries and virtually identical for national and international citations. However, it appears higher in electronics and machinery, compared to chemicals.

As already mentioned, R&D data are taken from the OECD-ANBERD database and are classified into 25 ISIC groupings¹⁸. This involves a relevant 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 matched data classified according to different classifications using the following methodology.

The Fraunhofer correspondence (Grupp and Munt, 1995) associates each of its 135 fields to a set of IPC classes and also to a set of SITC rev3 classes. We therefore first use the correspondence between SITC Rev3 and SITC Rev2 classifications¹⁹ and then matched each SITC rev2 code with ISIC Rev2 classes using the OECD correspondence tables²⁰. It has been employed because there is no direct correspondence between the SITC Rev 3 and ISIC Rev. 2 classifications and because R&D data from OECD-ANBERD are classified according to the ISIC Rev. 2 classification up to 1997.

With reference to the first correspondence (between SITC Rev3 and SITC Rev2

¹⁸ These are: Food, Beverages & Tobacco (31), Textiles, Apparel & Leather (32), Wood Products & Furniture (33), Paper, Paper Products & Printing (34), Chemicals excl. Drugs (351+352-3522), Drugs & Medicines (3522), Petroleum Refineries & Products (353+354), Rubber & Plastic Products (355+356), Non-Metallic Mineral Products (36), Iron & Steel (371), Non-Ferrous Metals (372), Metal Products (381), Non-Electrical Machinery (382-3825), Office & Computing Machinery (3825), Electric. Machin. excluding Commercial Equipment (3830-3832), Radio, TV & Communication Equipment (3832), Shipbuilding & Repairing (3841), Motor vehicles (3843), Aircraft (3845), Other Transport Equipment (3842+3844+3849), Professional Goods (385), Other Manufacturing (39).

¹⁹ This is available at: http://ec.europa.eu/eurostat/ramon/rerelations/index.cfm?TargetUrl=LST_REL

²⁰ This is available at: <http://www.maclester.edu/research/economics/page/haveman/Trade.Resources/tradeconcordances.html>

classifications), difficulties arise because the association between classes of different classification systems is not one to one and weights are not available. We therefore use OECD International Trade by Commodity Statistics (ITCS) data to obtain the relative weight of each SITC Rev3 class in the corresponding SITC Rev2 classes. The second correspondence (between SITC Rev2 and ISIC Rev2 classifications) then allows us to evaluate the weight of each SITC Rev.2 class into the corresponding ISIC Rev.2 classes. These weights differ across countries and across time. The combination of these weights finally allows us to map each of our 135 Fraunhofer fields into (a combination of) ISIC Rev.2 aggregate classes.

Because R&D data in the OECD-ANBERD database are classified according to the ISIC Rev.2 classification up to 1997 and to the ISIC Rev.3 classification afterwards, for the years following 1997 we use the correspondence between ISIC Rev.2 and ISIC Rev.3 in OECD (2005b). Once the correspondence has been established, R&D data are then finally obtained from current PPP dollar ISIC2 data in the OECD ANBERD database and computing real 1990 values using industry-specific deflators²¹.

5. Results

We suspect that variables on the right-hand side of equation (3.17) are non-stationary. We suspect also that shocks in the stock of knowledge and R&D should have a very persistent effect in 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 that exploits both the cross-section and the time series dimension of the data and also accounts for the short time series dimension. We then apply recent panel cointegration techniques to estimate equation (3.18).

5.1 Test of Unit Root

We use the test proposed by Harris and Tzavalis (1999), who derived a unit-root test that assumes that the time dimension, T , is fixed, which is more appropriate for our case. Their simulation results suggest that the test has favourable size and power properties for N greater than 25 (after excluding a few fields with rare patenting we end up with 768 cross-sectional units).

²¹ Implicit deflators are calculated as value added at current prices divided by value added volumes expressed in dollars (OECD STAN - Database). When we could not calculate the deflators because of missing values, we used data at more aggregated level.

The HT test statistic is based on the OLS estimator, in the regression model:

$$y_{it} = y_{i,t-1} + z'_{it}\gamma_i + \epsilon_{it} \quad (5.1)$$

where the term $z'_{it}\gamma_i$ allows for panel-specific means and trends. The asymptotic distribution of the test statistic is justified as $N \rightarrow \infty$.

Table 5.1 shows the values of the z statistic and the p-values. For each test two different specifications are displayed with and without trend. For all the variables in equation (3.17), we cannot reject the null of a unit root at any significance level. Indeed, r_{hit} , ns_{hit} , is_{hit} and a_{hit} all appear to be I(1). Our intuition 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 $ister_{hit}$ and $istra_{hit}$, which account for inter-fields and intra-fields international spillovers, respectively. These represent the two components of the international spillover variable and will be included in the regressions to evaluate their relative importance. Also for these variables we cannot reject the null of a unit root.

Finally we consider the first difference of the variable a_{hit} and test for the unit root of g_{hit}^A . 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_{hit}^A 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 international and the technological dimensions of 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 (3.17) and then, in the following section, we test that the residuals of this regression are stationary.

We use dynamic ordinary least squares (DOLS) to estimate (3.17) on a panel of 768

technology-country pairs²² and 21 years (Kao and Chiang, 2000). 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.

The DOLS estimator is based on the following decomposition of the time varying error component to be added to equation (3.17):

$$\varepsilon_{hit} = \sum_{k=-\infty}^{+\infty} \gamma'_k \Delta X_{hi,t+k} + v_{hit} \quad (5.2)$$

where ΔX_{hit} includes the first-differences of all the I(1) regressors and v_{hit} is orthogonal to all leads and lags of ΔX_{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 twenty-one years, that is it is fairly short and including too many leads/lags would significantly affect our estimates. As a consequence, we insert (5.2) with two lags and one lead into (3.18) and obtain the following cointegration relation:

$$a_{hit} = c_{hi} + \theta_{hi}t + \mu_1 r_{hit} + \mu_2 ns_{hit} + \mu_3 is_{hit} + \sum_{\substack{k=-2 \\ k \neq 0}}^{+1} (\gamma_{1k} \Delta r_{hi,t+k} + \gamma_{2k} \Delta ns_{hi,t+k} + \gamma_{3k} \Delta is_{hi,t+k}) + v_{hit} \quad (5.3)$$

where c_{hi} accounts for permanent differences in the innovation generating process of different country-technology pairs. Moreover we are able to split the international spillover pool into its intra-sectoral and inter-sectoral components. We add therefore to specification (5.3) the variable $istra_{hit}$, which accounts for intra-field international spillovers and the variable $ister_{hit}$, which accounts for inter-field international spillovers and obtain the following:

$$a_{hit} = c_{hi} + \theta_{hi}t + \mu_1 r_{hit} + \mu_2 ns_{hit} + \mu_4 istra_{hit} + \mu_5 ister_{hit} + \sum_{\substack{k=-2 \\ k \neq 0}}^{+1} (\gamma_{1k} \Delta r_{hi,t+k} + \gamma_{2k} \Delta ns_{hi,t+k} + \gamma_{4k} \Delta istra_{hi,t+k} + \gamma_{5k} \Delta ister_{hi,t+k}) + v_{hit} \quad (5.4)$$

²² 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 rare patenting. Overall, we exclude 2 fields for all countries (chemical 33 – Trash – and Machinery 25 - Packaging machines). We further exclude 13 fields for a single country (7 of these are excluded for the US).

As a robustness check, we then estimate the same equation including only two lags of the differenced terms, as in Kao et al. (1999). The results are very similar and, therefore, not reported in the tables.

The estimates of the parameters μ_1 , μ_2 , μ_3 , μ_4 and μ_5 are reported in Table 5.2, where we control for time trends by including heterogeneous (i.e. country-technology specific) time trends.

For the whole sample, our basic specification with no restrictions on time trends (column (1)) 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 0.07% increase in the domestically generated stock of scientific and technological knowledge. This is much smaller than the point estimate of the effect of own R&D obtained in previous studies²³. 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. Bottazzi and Peri (2007) find that a 1% increase of a country's R&D employment is associated with a 0.79% increase in the domestically generated stock of scientific and technological knowledge.

[Table 5.2 about here]

This discrepancy with previous results depends upon two main reasons. First, because of the different level of aggregation of R&D compared to patent data, our estimate of the elasticity of new knowledge to own R&D is reduced by λ , which is smaller than 1, by construction. Second, other country level studies do not account for the sectoral dimension (see, for example, Bottazzi and Peri, 2007) and are thus unable to distinguish between within fields effects (μ_1) and between fields effects (μ_2) at the national level. Put it differently, previously estimated country level elasticities of knowledge production to own R&D average out those two effects. Our preliminary results suggest that, although technology fields are heterogeneous, cross-fertilizations are at work and possibly relevant.

With reference to the elasticity of the stock of created knowledge to international

²³ 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.

spillovers, we find that this is equal to 0.23. Also in this case our estimate is affected (and reduced) by the presence of λ . Although we could compare the estimated coefficients $\hat{\mu}_1$ and $\hat{\mu}_3$, this comparison would not be appropriate as *is* includes both intra- and inter-fields effects.

In order to qualify our results, we therefore substitute the variable representing the international spillover pool with its two components: the variable *istra_{hit}*, which accounts for intra-field international spillovers only and the variable *ister_{hit}*, which instead accounts for inter-field international spillovers (column (2)).

The elasticity of the stock of knowledge to the intra-sectoral component of international spillovers is positive, significant and about two times the elasticity of the stock of knowledge to own R&D. This implies a much larger 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, as explained above, 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. Using the notation introduced in Table 2.1 our results therefore suggest that $C > A$.

By contrast to the above results, it is interesting to note that the elasticity of the stock of knowledge to the inter-sectoral component of international spillovers is about half of the elasticity of the stock of knowledge to national inter-sectoral spillovers (i.e. $B > D$). This suggests that proximity in the technology space and proximity in the geographical space are somewhat complementary: within field knowledge can easily be reached even if geographically distant, whereas absorption of relevant knowledge from different fields benefits from geographical proximity.

Taken together our estimates confirm that nationally generated R&D spillover effects (μ_1 and μ_2) tend to be larger than the international ones (μ_4 and μ_5) and that inter-sectoral R&D effects are strong and significant (μ_2 and μ_5) underlining that the distinction between inter-

sectoral and intra-sectoral is very important. Finally our results show that when we compare national and international R&D spillovers *within a technological field* (μ_1 and μ_4) the size of the latter is larger than the former.

5.3 Variations across different industries

As suggested by Jaffe and Trajtenberg (1996), Hall et al. (2001) and Bacchiocchi and Montobbio (2010) patterns of knowledge diffusion vary substantially across technological fields. We therefore perform separate regressions on the three industries: chemicals, electronics and machinery. These are also reported in Table 5.2.

The effects of national and international spillovers are indeed found to differ across industries. In the chemical industry the elasticity of new knowledge to national inter-sectoral external resources is significant and very high compared to the elasticity to own R&D and to international knowledge (column (3)). The importance of inter-sectoral spillovers in the chemical industry is further confirmed when we split the international spillover pool into its components (column (4)): the intra-sectoral component is not found to be significant, while the elasticity of the stock of knowledge to the international inter-sectoral spillover pool is positive and significant, although 2.5 times smaller than the elasticity of the stock of knowledge to the national (inter-sectoral) spillover pool.

By contrast, in the electronics industry inter-sectoral spillovers at both the national and international level are not found to significantly affect the stock of knowledge (column (6)). Only international intra-sectoral spillovers contribute to knowledge production and accumulation and its elasticity to them is six times larger than that to own R&D²⁴ (C>A). Indeed, the elasticity to own R&D in the electronics industry is much smaller compared to that in the chemical industry.

Finally substantial spillover effects are also present in the mechanical industry. However, the results for this industry tend to confirm the results for the whole sample and show that the spillover effect of cited international R&D on knowledge creation in a technological field is higher than the national one (0.7 vs 0.03). At the same time the international inter-sectoral spillover is much smaller than the national inter-sectoral one (1.34 vs. 0.19). In the Machinery industry therefore our results confirm that spillovers within specific technological fields have an international scope while intersectoral spillovers are enhanced by

²⁴ This is in line with Peri (2005) that shows that in the compute industry knowledge flows substantially farther.

geographical proximity.

The results reported above suggest that industries differ widely along the geographical reach and the sectoral specificity of spillovers. At the one extreme we find the electronics industry, in which knowledge flows are extremely sector-specific, but flow globally. At the other extreme we have the chemical industry, in which inter-sectoral flows are important, but occur mainly within national boundaries, implying a major role of geographical proximity for the diffusion of knowledge. The machinery industry falls in between: the responsiveness of knowledge production to inter-sectoral spillovers is geographically localized while sector specific knowledge flows internationally.

5.4 Test for cointegration

We need to check whether a_{hit} , r_{hit} , ns_{hit} and is_{hit} ($istra_{hit}$ and $ister_{hit}$) are indeed cointegrated. A test for cointegration is a test of stationarity of the residuals from the long run regression. We perform different cointegration tests developed in Pedroni (1999). These tests are either based on pooling along the within dimension or on 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 remaining statistics diverge to negative infinity under the alternative of cointegration, hence large negative values lead to rejection of the null of no cointegration. Four of the seven tests performed always reject the null of no cointegration at the 1% significance level (Tables 5.3 and 5.4). Four tests systematically confirm the existence of a cointegration relation as the two statistics systematically failing to reject the null of no cointegration are only here reported for completeness and not appropriate for our sample. Indeed, these are the panel-rho and the group-rho statistics and are shown by Pedroni (2004) to be undersized and to become overconservative in finite samples in which the N dimension exceeds the T dimension, as in our case. Our only concern is for the results on the panel-v statistics, which fails to reject in some instances. However, here we suffer from a problem due to the absolute size of T, as once

again Pedroni (2004) shows that the panel-v statistics tends to be undersized for small values of T.

[Tables 5.3 and 5.4 about here]

6. Final Remarks

Evidence that technology diffuses within and across industry and national boundaries is now well grounded. However despite the very large number of papers on knowledge spillovers and despite the relevance of the issue in terms of science and technology policy, it remains difficult to study and compare national, international, sectoral and inter-sectoral spillovers effects. Our paper builds a unified framework and tries to move one step forward in this direction.

Our analysis confirms the relevance of knowledge spillovers for innovative activity. It also confirms that both national and international R&D spillovers are effective in fostering patenting and that national R&D spillovers effects tend to be stronger than international ones. However our results also emphasize that, when the distinction between intra-field and inter-field spillovers is introduced, the estimated international spillovers effects within narrowly defined technological fields are more than twice the corresponding national ones.

This paper provides two contributions to the literature on spillovers. The first is that the geographical reach of knowledge spillovers is affected by the technological distance between the sender and the receiver: intra-sectoral knowledge flows are much less affected by distance than the inter-sectoral ones. Intra-sectoral spillovers flow globally because inventors and companies are better able to recognize and absorb external knowledge. By contrast, if innovating firms are active in technological fields different from the knowledge used for the current innovation, international spillovers are more difficult to extract. Here national borders matter because within these borders it is easier for innovators to identify, communicate and absorb those spillover that come from knowledge that is distant in the technological space.

The second contribution is that the type and extent of spillovers (in terms of the national/international and the intra-sectoral/inter-sectoral dimensions) vary across industries. We show that in the chemical industry inter-sectoral R&D spillovers are particularly important, but flow mainly nationally. On the contrary, in the electronics industry R&D spillovers mostly occur within the same technological fields and flow internationally. The machinery industry

falls in between.

These results further emphasize the need to disentangle knowledge spillovers in terms of knowledge types (codified vs tacit, simple vs complex) and channels of knowledge transmission. The relevance of international spillovers in the electronics industry point to the global dimension of the electronics sector and the variety of channels used for knowledge transmission, such as international RD collaborations, international mobility of skilled personnel, location of operations of multinational companies, outsourcing. On the contrary, the relevance of national intersectoral spillovers for the machinery sector may be related to the local user-producer relationships, usually co-located in specific geographical areas. Finally, the relevance of intersectoral, national spillovers for the chemical sector, confirm our hypothesis that when a sector acquires a substantial share of knowledge from other sectors not only inter-industry spillovers are stronger but also geographical proximity becomes very important.

These results call for new in depth-research on the causes of the differences in the global reach of the intra-sectoral spillovers compared to the inter-sectoral ones, and on the determinants of the variety across industries in the type and reach of spillovers.

7 Appendix

Table A.1 Correlation matrix of the explanatory variables used in the regressions and descriptive statistics

	a	rd	ns	is	istra	ister	Mean	Std.	Min	Max
a	1.00						4.78	1.67	0	10.31
rd	0.42	1.00					7.25	1.21	3.10	10.89
ns	0.24	0.60	1.00				1.62	1.40	0	9.11
is	-0.06	-0.36	-0.79	1.00			7.64	1.59	0	11.24
istra	0.15	-0.17	-0.57	0.65	1.00		4.12	2.10	0	11.24
ister	-0.25	-0.14	-0.03	0.15	-0.66	1.00	3.52	1.61	0	9.95

Table A.2 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 2.1. Typology of R&D Spillovers

	Intra-sectoral	Inter-sectoral
Intra-national	A	B
Inter-national	C	D

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

Country of applicant	Number of patents	% share
<i>Germany</i>	151421	22
<i>France</i>	56494	8
<i>UK</i>	47096	7
<i>Italy</i>	25230	4
<i>Japan</i>	159258	23
<i>US</i>	245972	36
Total	685471	100

Industry	Number of patents	% share
<i>Chemicals</i>	216661	32
<i>Electronics</i>	296326	43
<i>Machinery</i>	172484	25
Total	685471	100

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

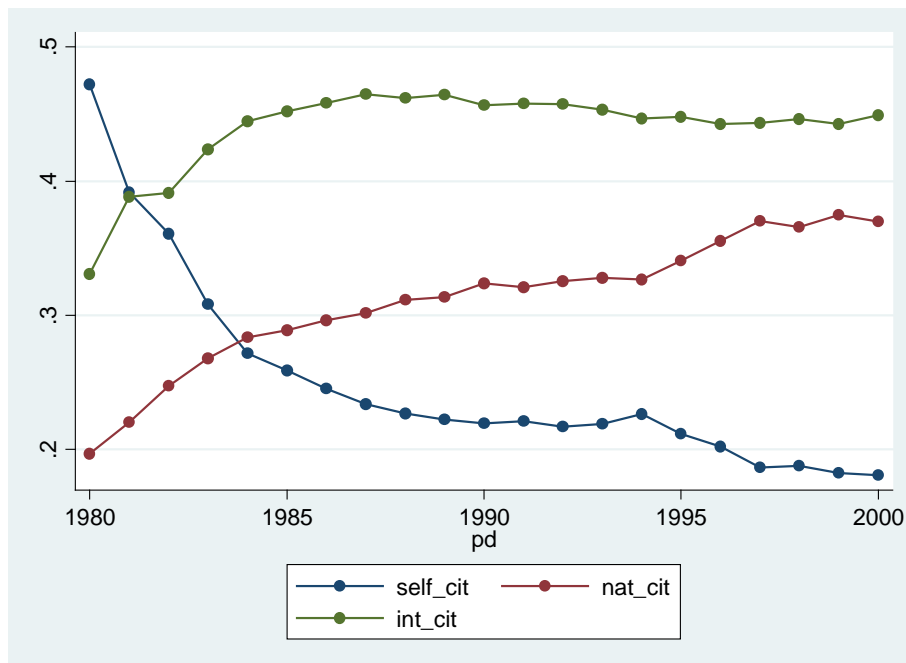


Table 4.2 Average number of citations per patent by type

Country^(*)	Citations		
	Self	National^(**)	International
<i>Germany</i>	0,44	0,52	0,94
<i>France</i>	0,34	0,24	1,13
<i>UK</i>	0,35	0,33	1,37
<i>Italy</i>	0,26	0,20	1,05
<i>Japan</i>	0,49	0,70	0,93
<i>US</i>	0,49	1,11	0,95
<i>All</i>	0,45	0,73	0,96

Industry^(*)	Citations		
	Self	National^(**)	International
<i>Chemicals</i>	0,61	0,75	1,06
<i>Electronics</i>	0,39	0,83	1,00
<i>Machinery</i>	0,36	0,53	0,76
<i>All</i>	0,45	0,73	0,96

(*) Country and Industry 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 first column.

Table 4.3 Percentage distribution of national and international citations

Country^(*)	National citations				International citations			
	Self	Others	Intra-field	Inter-field	Self	Others	Intra-field	Inter-field
<i>Germany</i>	0,45	0,55	0,63	0,37	0,02	0,98	0,61	0,39
<i>France</i>	0,57	0,43	0,66	0,34	0,02	0,98	0,63	0,37
<i>UK</i>	0,47	0,53	0,61	0,39	0,04	0,96	0,59	0,41
<i>Italy</i>	0,54	0,46	0,68	0,32	0,03	0,97	0,64	0,36
<i>Japan</i>	0,41	0,59	0,61	0,39	0,01	0,99	0,60	0,40
<i>US</i>	0,30	0,70	0,61	0,39	0,02	0,98	0,58	0,42
<i>All</i>	0,37	0,63	0,61	0,39	0,02	0,98	0,60	0,40

Industry^(*)	National citations				International citations			
	Self	Others	Intra-field	Inter-field	Self	Others	Intra-field	Inter-field
<i>Chemicals</i>	0,44	0,56	0,53	0,47	0,03	0,97	0,53	0,47
<i>Electronics</i>	0,31	0,69	0,66	0,34	0,01	0,99	0,64	0,36
<i>Machinery</i>	0,39	0,61	0,63	0,37	0,02	0,98	0,61	0,39
<i>All</i>	0,37	0,63	0,61	0,39	0,02	0,98	0,60	0,40

Columns "Self" and "Others" give the percentage distribution of national and international patents distinguishing between self citations and citations to patents held by other national or international firms, universities and public research centers. Columns "Intra-field" and "Inter-field" refer to the distribution of citations to patents held by other national or international firms between cited patents classified in the same technological field (intra-field) vs. a different technological field (inter-field).

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

Table 5.1 Test of Unit Roots

	Variables	<i>a</i>	<i>r</i>	<i>ns</i>	<i>is</i>	<i>istra</i>	<i>ister</i>	Δa
without trend	<i>z</i>	5.56	3.92	19.68	5.45	5.11	13.45	-1.4e+02
	p-value	1.00	1.00	1.00	1.00	1.00	1.00	0.00
with trend	<i>z</i>	12.97	8.79	30.98	13.92	9.18	20.85	
	p-value	1.00	1.00	1.00	1.00	1.00	1.00	

Note. Bold characters denote rejection of the null of a unit root at the 1% level.

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

Dependent variable: <i>a</i>	<i>All sample</i>		<i>Chemical</i>		<i>Electronics</i>		<i>Machinery</i>	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>R</i>	0.069*** (8.49)	0.066*** (8.20)	0.147*** (8.85)	0.100*** (6.04)	0.036*** (3.19)	0.033*** (2.91)	0.027** (2.21)	0.026** (2.08)
<i>ns</i>	1.274*** (13.69)	1.127*** (11.97)	2.48*** (17.05)	1.995*** (13.73)	0.076 (0.58)	0.096 (0.73)	0.950*** (4.04)	1.360*** (5.25)
<i>is</i>	0.227*** (11.11)		0.190*** (5.66)		0.128*** (3.45)		0.675*** (22.91)	
<i>istra</i>		0.157*** (6.71)		0.040 (1.07)		0.184*** (3.35)		0.715*** (23.13)
<i>ister</i>		0.484*** (7.78)		0.770*** (8.45)		-0.023 (-0.20)		0.190* (1.45)
Observations	16128	16128	7119	7119	4704	4704	4305	4305

Note. *t* statistics in parenthesis. All specifications include a heterogeneous time trend. DOLS obtained including two lags and one lead

Table 5.3 Test of cointegration – All sample

	<i>with is</i>	<i>with istra and ister</i>	<i>with is</i>	<i>with istra and ister</i>
panel v-stat	5.874	0.075	4.004	-1.034
panel rho-stat	4.551	10.780	11.024	15.989
panel pp-stat	-9.094	-10.169	-15.935	-20.744
panel adf-stat	-12.768	-12.753	-19.905	-21.697
group rho-stat	15.132	21.227	20.504	25.237
group pp-stat	-6.471	-9.062	-14.423	-23.975
group adf-stat	-16.425	-15.934	-23.207	-28.076
trend	NO	NO	YES	YES

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 5% level.

Table 5.4 Test of cointegration – industry regressions

<i>Chemicals</i>	<i>with is</i>	<i>with istra and ister</i>	<i>with is</i>	<i>with istra and ister</i>
panel v-stat	4.694	0.848	0.857	-2.790
panel rho-stat	1.560	6.381	6.604	10.984
panel pp-stat	-8.939	-8.578	-12.236	-12.525
panel adf-stat	-8.827	-9.336	-13.482	-13.141
group rho-stat	8.530	13.274	13.003	17.159
group pp-stat	-8.067	-8.349	-11.587	-14.073
group adf-stat	-11.749	-12.459	-16.380	-17.444
<i>Electronics</i>	<i>with is</i>	<i>with istra and ister</i>	<i>with is</i>	<i>with istra and ister</i>
panel v-stat	2.614	-0.875	2.910	0.342
panel rho-stat	2.848	6.065	6.310	8.335
panel pp-stat	-4.341	-5.055	-8.003	-11.841
panel adf-stat	-7.281	-6.034	-10.705	-11.992
group rho-stat	8.426	11.605	11.244	13.352
group pp-stat	-2.811	-4.354	-7.270	-13.520
group adf-stat	-8.745	-6.698	-11.266	-14.514
<i>Machinery</i>	<i>with is</i>	<i>with istra and ister</i>	<i>with is</i>	<i>with istra and ister</i>
panel v-stat	2.653	0.046	3.866	<i>1.613</i>
panel rho-stat	3.734	6.276	6.350	8.050
panel pp-stat	-1.703	-3.448	-6.490	-11.905
panel adf-stat	-5.817	-6.552	-10.177	-12.989
group rho-stat	9.511	11.885	11.212	12.824
group pp-stat	0.789	-2.252	-5.416	-14.175
group adf-stat	-7.541	-7.818	-12.079	-16.739
trend	NO	NO	YES	YES

Note. All reported values are distributed $N(0,1)$ under null of unit root or no cointegration

Bold (italic) characters denote rejection of the null of unit root (no cointegration) at the 5% (10%) level.