International Spillovers and Absorptive Capacity: A cross-country, cross-sector analysis based on European patents and citations*

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Abstract

This paper provides an empirical assessment of the effect of national and international knowledge spillovers on innovation at a finely defined sectoral level for six major industrialised countries over the period 1981-1995. International spillovers are always found to be effective in increasing innovative productivity. The paper then uses self-citations to investigate the role of prior R&D experience in enhancing a country's ability to understand and improve upon external knowledge (*absorptive capacity*). The empirical results show that absorptive capacity increases the elasticity of a country's innovation to both national and international spillovers. The larger the gap of a country with the technological leaders, the weaker is this effect, but the larger is the country's potential to increase it.

Keywords: R&D spillovers, absorptive capacity and patent citations.

JEL Classifications: O31, L60 and F12

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1. Introduction

Over the last decade, the theoretical literature on growth and trade has given considerable attention to the potential role of technological externalities in generating endogenous growth and determining patterns of trade. Attention has been mainly focused on the role of international spillovers for cross-country convergence in per capita income and changes in both technological and trade specialisation of countries. A growing empirical literature has addressed these issues, with contributions mainly differing along three lines, which correspond to three key questions: how do we measure knowledge spillovers? How do we assess their impact (i.e. which framework of analysis should we use)? Which level of aggregation is most appropriate for this assessment?

Knowledge external to a firm, a region or a country is obtained as a combination of R&D performed by other firms/regions/countries somehow weighted to account for the intensity of knowledge flows between the source and the destination. The measurement issue is in fact mostly related to the way such knowledge flows are inferred. Different solutions have been adopted, but since the work by Jaffe et. al. (1993) patent citations have come to be considered as the most informative tool for the purpose of tracing knowledge flows.

Regardless of the way external knowledge has been measured, its impact has been assessed mainly within two different frameworks, that is by introducing the chosen measure into an aggregate production function or into a knowledge production function, which gives the relationship between newly produced knowledge (often proxied by patents) and research inputs. In the first case the aim is to assess the impact of spillovers on productivity, while in the second case their effect is measured directly on innovation. Given that one of the main difficulties in assessing the impact of knowledge spillovers lies in separating their effects from that of rent externalities (Griliches, 1979), the second approach might be preferred to the first, although this is the one that has been mostly used in the literature.

Finally, with reference to the aggregation level adopted, studies within the micro-productivity literature have mostly performed analyses at the firm level, while studies within the trade-growth literature have used a high aggregation level, with countries or regions as the unit of analysis. Therefore there is a lack of analysis performed midway between these two extremes that takes into account differences across sectors within regions or countries (thus avoiding losing relevant knowledge flows in aggregation), while still accounting for homogeneities within such sectors. The present work takes this approach.

The impact of knowledge spillovers is here evaluated in a knowledge production function framework using data on European patents for six major industrialised countries (US, Japan, Germany, France, the UK and Italy) over the period 1981-1995. I use patent citations to trace knowledge flows within and across countries among 135 micro-sectors in the chemicals, electronics and machinery industries. Such flows are then used to estimate the effect of national versus international knowledge spillovers in the different industries.

Results from different empirical studies seem to suggest that knowledge spillovers are mainly intranational rather than international in scope[1]. In one of these studies, Maurseth and Verspagen (2002) employ citations by patent applications at the European Patent Office (EPO) to trace knowledge flows across European regions: they find that patents are more likely to cite other national patents rather than foreign patents. In this paper I show that this result arises because cross citations between European regions exclude all citations

[1] See, for example, Jaffe et al. (1993), Branstetter (2001), Maurseth and Verspagen (2002), Peri (2003).

directed towards the world technological leaders (US and Japan). Once these are included in the analysis the home country effect disappears and the share international citations is found to be particularly high in countries below the technological frontier. Consistently, international spillovers are always found to be effective in increasing innovative productivity.

The paper then addresses a second issue, so far often neglected in the literature: the positive externality generated by international technology flows will crucially depend on the destination country's ability to understand and exploit external knowledge. Such ability is a function of the country's past experience in research, an idea analogous to the concept of *absorptive capacity* introduced by Cohen and Levinthal (1990) in the context of firms' learning and innovation.

The role of prior R&D experience in improving the ability of firms to understand and employ external knowledge has only been investigated in a few studies so far (see Griffith, Redding and Van Reenen, 2001; Griffith, Harrison and Van Reenen, 2003). The novelty here lies in the use of self-citations to measure the effect of absorptive capacity in enhancing the ability to benefit from spillovers. A self citation indicates that the firm did some research in the past and that it has now generated a new idea building upon previous research in the same or in a related technology field. As such, self citations are a clear indication of accumulation of knowledge internal to the firm.

The empirical results show that absorptive capacity increases the elasticity of a country's innovation to both national and international spillovers. However, its effect is different depending on the position of the country with respect to the world technological frontier: the larger the gap of a country with the technological leaders, the lower is its ability to absorb and exploit external knowledge, but the larger is its potential to increase this ability.

The paper is organised as follows. Section 2 reviews the relevant literature on the topic. Section 3 presents the empirical model, while section 4 discusses the data used in the empirical analysis and describes some stylised facts emerging from them. Section 5 then reports the estimation results. Section 6 concludes.

2. Related literature

Spillovers and R&D externalities have been one of the most active areas of research in economics over the past thirty years. The reason for the still lively interest in the topic lies in their importance for growth theory and for the explanation of productivity growth. Without the social increasing returns originated by R&D externalities it is unlikely that economic growth can proceed at a constant, undiminished rate of return in the future. Moreover, the reach of spillovers has important implications for cross-country convergence in living standards. In the recent years, interest has gradually shifted to this last issue and significant research effort has been devoted in trying to assess the relevance of international spillovers and how they can be enhanced.

2.1 Knowledge spillovers: definition and measurement

In a pioneering paper, Griliches (1979) identifies two main sources of potential externalities generated by R&D activities: rent spillovers and pure knowledge spillovers. Rent spillovers arise when the prices of intermediate inputs purchased from other firms or countries are not fully adjusted for quality improvements resulting from R&D investment. As such, they originate from economic transactions and are the consequence of measurement "errors".

By contrast, pure knowledge spillovers arise because of the imperfect appropriability of ideas: the benefits of new knowledge accrue not only to the innovator, but "spill over" to other firms or countries, thus enriching the pool of ideas upon which subsequent innovations can be based. Hence, knowledge spillovers may occur without any economic transaction and are not the manifestation of any measurement problem.

Although the distinction between the two concepts of spillovers seems clear from the theoretical point of view, their empirical identification is far more problematic. One reason for this ambiguity is that economic transactions that originate rent spillovers may also imply some knowledge transfer[2]. Further difficulties arise because innovation by competitors may also generate strategic effects. If technological rivalry is strong and means of appropriation are effective (e.g. the scope of patent protection is wide), firms might find themselves engaged into a race for the appropriation of new profitable ideas (*patent race*). As a consequence, the positive technological externality arising from other firms' research can potentially be confounded with a negative affect due to competition[3].

Notwithstanding these difficulties, the widespread interest in the economic implications of the existence, the magnitude and the reach of knowledge spillovers has spurred a large empirical literature. Authors have followed various approaches in the attempt to estimate the effect of spillovers. The most widely used has been to introduce a measure of the potential pool of external knowledge into a standard production function framework, either at the firm or at a more aggregate (industry, region, country) level, with the ultimate aim to assess the impact of accessible external R&D on total factor productivity (TFP). However, difficulties in measuring prices precisely and adjusting them for quality improvements make this approach not particularly suited to distinguish technological externalities from pecuniary externalities.

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[2] Together with transactions in intermediate inputs, Cincera and Van Pottelsberghe de la Potterie (2001) identify two more channels through which rent spillovers potentially operate: transactions in investment goods and the use by one firm/country of patents granted to other firms/countries. This last channel is most likely to carry knowledge spillovers as well.
[3] Jaffe (1986) and Brandstetter (2001) have found evidence of this negative effect.

For this reason, some authors have adopted the *knowledge production function* (KPF) methodological framework initiated by Pakes and Griliches (1984)[4]. Within this framework research efforts and knowledge spillovers are mapped into knowledge increments, most often proxied by patents. Since the production of innovation (patents) does not require intermediate inputs and is not evaluated using prices, but simply the quantity of innovations, it minimises the role of rent externalities.

Both frameworks rely on the assumption that knowledge externalities are realised into two steps[5]. Knowledge flows represent the first step and take place whenever ideas generated by a firm/country are learned by another firm/country. Such learning creates a pool of accessible external knowledge, which then has a positive impact on productivity, however measured (this is the second step). A key issue in the empirical analyses on knowledge spillovers is then the measurement of the pool of external knowledge. This is usually built as the amount of R&D conducted elsewhere weighted by some measure of proximity in the technological or geographical space, taken to be representative of the intensity of knowledge flows between the source and the recipient of spillovers.

Different proximity measures have been employed in the literature. A first simple one was used by Bernstein and Nadiri (1989) who built the pool of knowledge external to a firm as the unweighted sum of the R&D spending by other firms in the same industry. This measure is fairly unsatisfactory as it assumes that a firm equally benefits from R&D of all other firms in the same industry and does not benefit at all from R&D conducted by firms in other industries. Results on spillovers based on industry measures like this might also

[4] Brandstetter (2001), Bottazzi and Peri (2003) and Peri (2003) are some of the most recent applications of this framework.

[5] Peri (2003) makes this distinction very clear.

capture spurious effects due to common industry trends and shocks.

A more sophisticated and commonly used measure of technological proximity was first introduced by Jaffe (1986). Each firm is associated to a vector describing the distribution of its patents across technology classes or its R&D spending across product fields. Such vector represents the firm's location in a multi-dimensional technology space. Proximity between two firms is then obtained as the uncentred correlation coefficient between the corresponding location vectors.

Although this measure is less likely to be contaminated by pecuniary externalities and common industry effects, evidence of its positive effect on productivity may still be unrelated to knowledge spillovers, but rather be the result of "spatially correlated technological opportunities" (Griliches, 1996)[6]. In trying to overcome these problems the most recent studies have been using a new and potentially rich source of information represented by patent citations.

Patent documents also include references to previous patents (citations) with the fundamental legal purpose to indicate which part of the knowledge described in the patent is actually claimed in the patent and which parts have been claimed by earlier patents. However, following Jaffe et al. (1993), citations can be taken as a paper trail of knowledge flows: a reference to a previous patent indicates that the knowledge of that patent was in some way useful for developing the new knowledge described in the citing patent.

For this reason, citations provide the opportunity to avoid relying on ad hoc proximity measures and look directly at the process of knowledge diffusion.

[6] Technological proximity is likely to be correlated with exogenous technological opportunity conditions. If new opportunities exogenously arise in a technological area, firms active in that area will all increase their R&D spending and improve their productivity. This would erroneously show up as a spillover effect.

Maurseth and Verspagen (2002) use citations by European patents to obtain estimates knowledge flows across European regions. Peri (2003) does a similar exercise using data on a panel of European and North American regions and then uses the obtained estimates to build a measure of accessible external R&D and assess the impact of spillovers within and across regions.

2.2 International knowledge spillovers

Over the last few years a great attention has been devoted to estimating the importance of international knowledge spillovers[7]. From the theoretical point of view, the interest in the reach of knowledge externalities lies in their implications for endogenous growth, trade and convergence.

If barriers to knowledge flows exist, then regions or countries' knowledge stocks may accumulate in proportion to local industrial and research activity. Increasing returns resulting from spillovers are then bounded within geographical limits and cross-country differences in levels of per capita income and in trade patterns will be persistent. By contrast, perfect technology diffusion favours the convergence of per capita output levels and leaves factor endowments as the sole determinants of trade patterns (Grossman and Helpman, 1991).

The most influential contribution in the empirical literature on the topic has been the paper by Coe and Helpman (1995). They use country level data on trade shares as a proxy for the intensity of knowledge flows between countries and find that international spillovers from foreign R&D positively affect productivity growth and that this effect is larger for small countries. The previous discussion on rent spillovers should make clear why several authors have questioned Coe and Helpman's methodology to infer flows of knowledge

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[7] A detailed survey on the topic can be found in Cincera and Van Pottelsberghe de la Potterie (2001).

from flows of goods. In particular, Keller (1998) provides econometric evidence that casts doubt on the effectiveness of trade as a mechanism for knowledge transfer, finding higher coefficients on foreign R&D when using random weightings instead of those used by Coe and Helpman (1995), based on trade shares.

Eaton and Kortum (1996, 1999) pursue a different line of research and derive a formal model of technology diffusion. They identify knowledge flows through cross country patenting and find that spillovers decline with geographical distance. They also show that trade is not an important channel of technological diffusion and that a country's level of education plays a significant role in the ability to absorb foreign ideas.

In a recent contribution, Bottazzi and Peri (2003) use European patent and R&D data to estimate a knowledge production function on a cross-section of European regions. They use a measure of proximity based on the geographical distance to weight R&D external to a region and find that spillovers are localised and exist only within a distance of 300 km.

Brandstetter (2001) casts doubt on the usefulness of econometric work performed at such a high level of aggregation: results obtained in such a setting are likely to reflect common demand or input price shocks or a common time trend and obscure any effect of knowledge spillovers. He argues that within countries and even within 2-digit industries there is considerable technological heterogeneity and hence performs his analysis using data on a panel of firms from US and Japan. He estimates of the impact of national and international spillovers within a knowledge production function framework, using Jaffe's uncentred correlation coefficient as a proximity measure. His results show that spillovers are more intranational than international in scope, though Japanese firms appear to benefit from the R&D of US firms to some extent.

Among the first papers to employ patent citations to study the issue of cross-border mobility of knowledge, Jaffe et al. (1993) and Jaffe and Trajtenberg (2002, chapter 7) find that a patent is typically 30 to 80 percent more likely to cite other patents whose inventors reside in the same country, than patents from other countries. This suggests that cross-border mobility of knowledge is limited and that knowledge spillovers are localised.

Maurseth and Verspagen (2002) use citations between European regions to estimate the effect of geographical distance on knowledge flows. Their results indicate that geographical distance has a negative impact on knowledge flows and that this impact is substantial. They find knowledge flows to be larger within countries than between regions located in separate countries, as well as within regions sharing the same language (but not necessarily belonging to the same country). Their results also indicate that knowledge flows are industry specific and that regions technological specialisation is an important determinant for their technological interaction as spillovers producers or receivers.

In a similar study, using the NBER patent and citations data, Peri (2003) finds that only fifteen percent of average knowledge is learned outside the region of origin and only nine percent outside the country of origin. However, his results suggest that knowledge in highly technological sectors (such as computers) and knowledge generated by technological leaders (top regional innovators) flow substantially farther. Further, compared to trade flows knowledge flows reach much farther and external accessible knowledge is found to have a strong impact of innovation as measured by patent counts.

In concluding this section, I note that other authors have followed alternative approaches to the measurement of knowledge spillovers. Some works have used flows of foreign direct investment (FDI) to proxy for knowledge flows. Since FDI implies movement of capital and know-how, it has long been considered a mean of knowledge transfer and several studies find that FDI does indeed facilitate spillovers.

2.3 Benefiting from spillovers: the role of absorptive capacity

Recent research has started to be concerned with the ability of firms and countries to benefit from spillovers. The presumption is that firms and countries can understand external knowledge and build upon it only if they have a sufficient level of prior own knowledge and research experience.

> "*A critical component of the requisite absorptive capacity for certain types of information, such as those associated with product and process innovation, is often firm specific and cannot be bought and quickly integrated into the firm. (...) Moreover, as Nelson and Winter's (1982) analysis suggests, much of the detailed knowledge of organizational routines and objectives that permit a firm and its R&D labs to function is tacit. As a consequence, such critical complementary knowledge is acquired only through experience within the firm*" (Cohen and Levinthal, 1990, p. 135).

Along these lines, some recent papers have started to investigate the role of prior R&D experience in improving the ability of firms to understand and employ external knowledge. This issue deserves attention because if spillovers do have the potential to improve a country's growth performance, then it is important to understand the mechanisms by which they can be enhanced and made more effective.

Findings on the relevance of the absorptive capacity argument have so far been controversial. Griffith et al. (2001) use a panel of industries across twelve OECD countries to investigate whether domestic R&D, in addition to stimulating innovation, also enhances knowledge spillovers and find that domestic R&D does facilitate technology catch-up.

More recently, Griffith et al. (2003) use a sample of UK manufacturing firms to examine the role of knowledge spillovers associated with technology sourcing. They include measures of domestic and foreign external knowledge stock into the firm level production function and allow the elasticity of value added with respect to these stocks to depend on a measure of absorptive capacity and a measure of the geographical location of firms innovative activities. Although their data do not allow them to distinguish between the absorptive capacity effect and the technology sourcing effect, their results seem to suggest the latter to be more likely to affect spillovers, while the absorptive capacity effect appears quite weak.

3. The empirical model

I assume that in country *h* firms operating in micro-sector *i* produce new knowledge using both their own R&D and external knowledge originated either elsewhere in the same country or in another country. This idea is embodied into a production function of innovation or new knowledge:

$$Q_{hit} = f(R_{iht}, NS_{iht}, IS_{iht}, \theta, \nu_{iht}) \tag{1}$$

where Q_{iht} is some latent measure of new technological output in micro-sector *i*, country *h* at period *t*, R_{iht} measures the corresponding R&D investment, NS_{hit} is the domestic spillover pool, IS_{iht} is the foreign spillover pool and θ is the vector of unknown technology parameters.

I assume that the knowledge production function above is a Cobb-Douglas

$$Q_{iht} = R_{iht}^{\alpha} \cdot NS_{iht}^{\beta} \cdot IS_{iht}^{\gamma} \Phi_{hc} e^{\nu_{hit}} \tag{2}$$

where $\theta \equiv (\alpha, \beta, \gamma)$, ν_{hit} is an error term and Φ_{hc} captures country and industry specific effects[8] (as, for example, the set of opportunity conditions) through a set of dummy variables:

$$\Phi_{hc} = e^{\sum_h \delta_h D_{ih} + \sum_c \delta_c D_{ic}} \qquad (3)$$

3.1 Knowledge spillovers

Estimation of equation (2) entails a series of measurement issues. The first issue relates to the measurement of the knowledge spillover variables. In the present context this involves tracing the direction and intensity of knowledge flows across micro-sectors and countries.

Knowledge flows and R&D spillovers or externalities are two distinct phases of one phenomenon, one following the other. Knowledge flows represent the first step, which takes place whenever knowledge generated by an economic agent (typically a firm) is learned by another agent elsewhere located. This diffusion process generates a stock of knowledge accessible to the recipient agent, which, through learning, then generates a positive externality on his productivity (hence the name "spillover pool"). While R&D externalities necessarily require knowledge flows to arise, knowledge flows do not automatically produce R&D externalities.

I follow the approach initiated by Jaffe et al. (1993) and use patent citations for the purpose of tracing the direction and intensity of knowledge flows. Each patent document includes citations to previous patents that are relevant to the idea the patent is meant to protect. This establishes a close relationship between knowledge flows and patent citations: they reveal that the researchers who developed the idea knew about the ideas contained in the cited patents and that such ideas were relevant in the research process leading to the new discovery.

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[8] Assume that micro-sector i belongs to industry c ($i \in c$).

Unfortunately, not all the citations in a patent document are included by the inventors: some are added by the reviewers during the examination process each patent application has to go through in order to establish the novelty, originality and potential use of its content. These added citations do not necessarily reveal ideas known to the inventor. However, Jaffe et al. (1993) argue that reviewers, who are experts in a technological area, do a systematic search in that area so that this should not induce any distortion in the technological and geographical pattern of citations. Hence, I can assume that citations added by the reviewers simply add noise to the relation between knowledge flows and patent citations.

I use the information on the direction of knowledge flows implied by the pattern of citations with reference to both the technological and geographical space. For each country I consider all citations made by patents classified into each micro-sector i. I then identify the micro-sectors the cited patents belong to (i.e. their direction in the technological space) and whether they are held by other firms/institutions located in the same country (*national* citations), or by firms/institutions located in a different country (*international* citations). I also identify all citations directed to other patents held by the citing firm (*self* citations). Finally, I account for the intensity of knowledge flows using relative numbers of citations.

National spillovers are measured in the following way:

$$NS_{iht} = \prod_{j \neq i} R_{jht}^{nc_{hij}} \qquad (4)$$

where nc_{hij} is the relative number of citations from patents classified into micro-sector i to patents classified into micro-sector j and held by other firms/institutions in the same country h[9]. The product is over $j \neq i$ because spillovers within the same micro-sector are already included into the own RD measure, hence their effect cannot be distinguished from that of own RD: for this reason equation (4) gives a measure of the national inter-sector pool of knowledge spillovers. Note further that this measure is obtained using only citations to *other* national firms and institutions, hence abstracting from self-citations, which cannot be regarded as a "paper trail" of knowledge flows and which account for a large proportion of overall national citations, as will be shown in the next section.

In calculating the relative number of citations I pool all citations made by patents classified in a micro-sector throughout the relevant sample period. This is equivalent to assuming constant flows for different years, an assumption which has been found to be supported by the data in a similar context (see Peri, 2003)[10].

International spillovers are measured in a similar way to the national spillovers:

$$IS_{iht} = \prod_{j} FR_{jht}^{ic_{hij}} \qquad (5)$$

where ic_{hij} is the relative number of citations from patents applied for by firms in country h and classified into micro-sector i to patents held by firms/institutions in a different country and classified into micro-sector j[11]. FR

[9] Some recent work by Peri (2003) tries to estimate the direction and intensity of knowledge flows from patterns of citations, rather than assuming that they may be represented by such patterns as we do here, along the lines of the micro-productivity literature.

[10] The advantage of this assumption is that it reduces the number of zeros in the data; the price is that of a higher serial correlation in the knowledge spillover variables, which is however a common feature in the empirical literature.

[11] Note that the way I have defined national and international spillovers in (4) and (5) is less common in the microeconomic literature, where they are usually defined as a weighted average of R&D resources. The root I follow here is more common in the macroeconomic

stands for foreign R&D and is defined as:

$$FR_{jht} = \prod_{f \neq h} R_{jft}^{rc_{hf}} \tag{6}$$

where rc_{hf} is the relative number of international citations from patents held by firms in country h that are directed to patents belonging to firms or institutions resident in country f. Contrary to the national spillover measure, equation (5) includes both the international intra- and inter-sector pools of knowledge spillovers.

3.2 The basic specification

Substituting (4) and (5) into (2), the knowledge production function becomes:

$$Q_{iht} = R_{iht}^{\alpha} \cdot \prod_{j \neq i} R_{jht}^{\beta \cdot nc_{hij}} \prod_{j} FR_{jht}^{\gamma \cdot ic_{hij}} \Phi_{hc} e^{\nu_{iht}} \tag{7}$$

Equation (7) says that innovation in each micro-sector i in country h results from a Cobb-Douglas combination of R&D resources there used and R&D resources used in other micro-sectors and other countries. The elasticity of innovation to R&D resources other than own is then proportional to the intensity of knowledge flows between micro-sectors and countries as measured by citations.

Note that, following Branstetter (2001), I have only current own and external R&D in the knowledge production function, while one might suppose that they should enter with a long lag. With reference to own R&D, this is justified by the empirical finding that the strongest relationship between R&D and patent applications is contemporaneous (Hall, Griliches and Hausman, 1986). Furthermore, distributed lags on R&D, which is highly persistent in time, might

literature (see Bottazzi and Peri, 2003, for a similar application).

induce a near-multicollinearity problem in the estimation[12].

Empirical research has also found evidence consistent with rapid diffusion of innovations (Caballero and Jaffe, 1993). Mansfield (1985), for example, finds that 70 percent of new product innovations "leak out" within one year and only 17 percent take more than 18 months.

There is a second measurement issue I need to deal with in order to estimate equation (7): this relates to the measurement of technological output. Since there is no direct measure of innovation I assume that some fraction of the new knowledge is patented, such that the number of new patents generated in micro-sector i, P_{iht}, is an exponential function of its new knowledge:

$$P_{iht} = Q_{iht} e^{\sum_h \vartheta_h D_{ih} + \sum_c \vartheta_c D_{ic} + \eta_{ih}} \tag{8}$$

This is a common assumption in the knowledge production function literature[13] and in the broader innovation literature, where patents have long been considered as the best available measure of output of innovative activity. The caveats of using patent data as a measure of innovation have been widely discussed in the literature and a good reference is Griliches (1991)

Equation (8) controls for country specific effects and includes a set of industry dummies to account for industry-level differences in the propensity to patent, which might be related to the usefulness of patents as a tool of appropriation in

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[12] 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). In this case, it can be easily shown that such measure is 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 micro-sector i ($i \in$ I).

[13] See, for example, Pakes and Griliches (1984), Branstetter (2001), Bottazzi and Peri (2003).

industry c. Finally, equation (8) also includes individual effects, η_{ih}, to account for heterogeneity within industries and to allow for differences in the propensity to patent in each micro-sector.

Substituting (7) into (8) and taking logs I obtain my basic specification:

$$p_{iht} = \alpha \cdot r_{iht} + \beta \cdot ns_{iht} + \gamma \cdot is_{iht} + \sum_h \phi_h D_{ih} + \sum_c \phi_c D_{ic} + \eta_{ih} + \nu_{iht} \qquad (9)$$

where p_{iht} is the log of the number of patents, r_{iht} is the log of own R&D and

$$ns_{iht} = \sum_{j \neq i} nc_{hij} \ln R_{jht} \qquad (10)$$

$$is_{iht} = \sum_{i} ic_{hij} \sum_{f \neq h} rc_{hf} \ln R_{jft} \qquad (11)$$

The coefficients of the industry dummy variables in equation (9) now represent industry level differences in the propensity to patent, which are functions of both the level of technological opportunity and of appropriability conditions.

I cannot directly estimate equation (9) because R&D data is not available at the same low aggregation level available for patents and citation data. R&D data is available for the 25 ISIC Rev. 2 manufacturing sectors reported in Table A.1 in the Appendix, however given the focus of the present work on technologies in chemicals, electronics and machinery industries, only data for fifteen ISIC Rev. 2 sectors have been used as explained in the appendix.

In order to deal with this data limitation problem, I make the following assumption:

$$R_{iht} = R_{Iht}^{\lambda} \mu_{ih} \quad \text{where } i \in I \text{ and } \mu_{ih} = e^{\xi_{ih}} \qquad (12)$$

Hence, I assume that (the logarithm of) R&D expenditures within a micro-sector are a portion λ of (the logarithm of) R&D expenditures within the ISIC industry the micro-sector belongs to. This portion is assumed to be the same for all micro-sectors: differences across them are accounted for by a fixed effect component, μ_{ih}[14]. Using (12) in equation (9) the basic specification I can estimate is:

$$p_{iht} = \alpha\lambda \cdot r_{Iht} + \beta\lambda \cdot ns^{*}_{iht} + \gamma\lambda \cdot is^{*}_{iht} + \sum_{h}\phi_h D_{ih} + \sum_{c}\phi_c D_{ic} + \varepsilon_{ih} + \varepsilon_{iht} \quad (13)$$

where ns^{*}_{iht} and is^{*}_{iht} are calculated as in (10) and (11), but using the more aggregated R&D data[15].

Note that the coefficients on own R&D and the spillover variables are all multiplied by λ, which is smaller than one by assumption. This should result in estimates of the elasticities that are smaller than those found in the literature[16].

It should also be mentioned that we do not observe the pure effects of knowledge spillovers on innovation by firms within a sector, which are an unambiguous positive externality. Rather, as Jaffe (1986) and, more recently, Branstetter (2001) have noticed, we observe the effects of knowledge spillovers

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[14] I abstract from any random time variation, given the well known relative stability of R&D expenditures over time.

[15] The individual effect in equation (13) include elements which involve summations of (weighted) individual effects components of other micro-sectors in both home and foreign countries:

$$\varepsilon_{ih} = (\alpha\xi_{ih} + u_{ih}) + \beta\sum_{i \neq j} nc_{hij}\xi_{hj} + \gamma\sum_{j} ic_{hij}\left(\sum_{f \neq h} rc_{hf}\xi_{fj}\right)$$

Since these summations are fixed in time for each '*ih*' I can include them into an overall individual effect without loss of generality.

[16] Estimates obtained elsewhere in a similar framework (e.g. Brandstetter, 2001) are however difficult to compare to those obtained here because the micro-productivity literature has been focussing on firm-level data.

on patents, which are not only the economic manifestation of firms' innovation, but also a tool of appropriation.

If technological rivalry among the firms is intense enough and the scope of intellectual property rights is broad enough, then firms may sometimes find themselves competing for a limited number of available patents in a patent race. As a consequence, together with a positive technological externality there might be a negative effect of other firms' research due to competition. This might then result in negative estimates of the elasticities of patents to the spillover variables even though the underlying knowledge externality is positive.

In estimating equation (13) my focus will be on assessing the relevance of inter-sector and of international spillovers and on establishing differences across the three industries the data in the sample belong to: chemicals, electronics and machinery. While the idea of assessing the importance of international spillovers has received great attention in the literature over recent years, studies in the field have rarely tried to evaluate the relevance of international spillovers across different sectors and the relevance of inter-sector spillovers has not been clearly assessed yet.

3.3 Knowledge accumulation at the firm level and absorptive capacity

The idea that knowledge generated by an economic agent flows to a different location and is learnt by some other agent crucially relies on the assumption that knowledge is, at least partially, a public good. It is however recognised that the ability to learn external knowledge often requires prior own experience. This is the well known concept of *absorptive capacity*, that is the idea that "*the more the findings in a field build upon previous findings, the more necessary is an understanding of prior research to the assimilation of subsequent findings*" (Cohen and Levinthal, 1990, p. 140).

The role of prior R&D experience in improving the ability of firms to understand and employ external knowledge has been investigated in some recent papers. While these papers examine the role of absorptive capacity in a TFP growth framework (Griffith, Redding and Van Reenen, 2001) or in a firm production function setting (Griffith, Harrison and Van Reenen, 2003) I can here directly assess its relevance on a country's innovative performance using information on self citations.

A self citation indicates that the firm did some research in the past and that it has now generated a new idea building upon previous research in the same or in a related technology field. As such, self citations are a clear indication of accumulation of knowledge internal to the firm. The higher the average number of self citations in a micro-sector the more firms operating (i.e. innovating) within such micro-sectors build upon internal knowledge in generating new ideas.

If the absorptive capacity argument is correct, then such firms should also display a higher ability to understand and exploit external knowledge. A way to formalise this is to allow the elasticity of innovation (patents) to spillover pools to depend on the chosen measure of absorptive capacity. This assumption is analogous to the one made by Griffith, Harrison and Van Reenen (2003) on the elasticity of value added to the domestic and foreign external knowledge stock. In this case the aim is to assess whether the elasticity is indeed higher the more firms have been engaged into R&D activities in the same or in related technological areas.

Hence we can write of the elasticity of patents to the national spillover pool (β) and their elasticity to the international spillover pool (γ) as:

$$\beta = \beta_0 + \beta_1 \cdot self_{iht}$$
$$\gamma = \gamma_0 + \gamma_1 \cdot self_{iht} \quad (14)$$

where $self_{iht}$ is the number of self citations per patent in micro-sector i, in country h at time t. Differently from Griffith et al. (2003), I am not imposing the restriction that firms' absorptive capacity affects their ability to pick up domestic and foreign spillovers equally ($\beta_1=\gamma_1$). This is because the two spillover variables have a different "meaning": the national spillover pool here only includes inter-sector spillovers, while the international spillover variable captures the effect of both intra- and inter-sector spillovers.

Using then the expression for the elasticities to spillovers given in (14), the full specification now becomes:

$$p_{iht} = \alpha\lambda \cdot r_{Iht} + \beta_0\lambda \cdot ns^*_{iht} + \gamma_0\lambda \cdot is^*_{iht} + \beta_1\lambda \cdot (ns^*_{iht} \cdot self_{iht}) + \gamma_1\lambda \cdot (is^*_{iht} \cdot self_{iht}) + \theta \cdot self_{iht} + \sum_h \phi_h D_{ih} + \sum_c \phi_c D_{ic} + \varepsilon_{ih} + \varepsilon_{iht} \quad (15)$$

4. The data

I use patent applications[17] at the European Patent Office (EPO) and their citations, both from the EPO/CESPRI database. The analysis focuses on applications at the EPO over the period 1981-1995 by firms located in 6 countries: France, Germany, Italy, Japan, the UK and the US.

A patent document contains a detailed description of the innovation and indicates the technological class (IPC) it belongs to; it also includes the name and address of the inventor (usually one or more individuals) and of the applicant (most often a firm or an institution). Here I assign each patent to the country of residence of the applicant and consider only patent applications by

[17] In what follows, whenever I refer to patents, I mean patent applications.

firms, thus excluding individual applicants and public institutions.

Although the EPO/CESPRI database contains all patent applications (and their citations) at the EPO up to 2003, I have chosen to limit the analysis to the above countries and to the 1981-1995 period because for this selected sample all firms applying for a patent at the EPO over have been carefully identified and have been assigned a code. This is relevant for correctly detecting patterns of citations, as I shall later explain.

It should be noted that European patent data have been used less extensively than US patent data in the spillovers literature and that there are important differences between the two patent systems. Differently from the US Patent and Trademark Office (USPTO), the EPO acts as a single intermediary to all participating countries. Innovators may apply for a European patent up to one year after applying to their national patent office, and in most cases applications at the EPO do follow this two-stage procedure.

The national application procedure and the additional costs required to file an application at the EPO both act as a sieve that selects "good" inventions. For this reason, European patents are considered to be of higher average quality. However, the additional costs involved might induce a bias against small firms, which might then underestimate the level of localisation, if localised (national) spillovers are more important for small firms.

R&D data are taken from the OECD-ANBERD database. This entails a classification problem in that patents are classified according to the technology-based IPC classification, while R&D is classified according to the product-based ISIC classification. In order to overcome this problem, I use two different concordances: the first between the IPC and the SITC Rev. 2 (provided by Grupp-Munt, 1997), the second between the SITC Rev. 2 and the ISIC Rev.2, which I built using the OECD concordance[18].

Based on these concordances, I obtain 135 micro-sectors that represent my unit of analysis. These micro-sectors are analogous to product groupings and have the advantage that can be themselves grouped into three major industries: Chemicals (61 micro-sectors), Electronics (38 micro-sectors) and Machinery (36 micro-sectors). These are industries with high average R&D/sales ratio and where technological innovation is an important phenomenon, hence where it is more likely to identify the sources and effects of spillovers and of knowledge accumulation within the firm.

Table 1. Number and distribution of patents in the sample by applicant's country of residence and by industry

Country	**Number of patents**	**% share**	**Average micro-sector size**
Germany	86228	22.6	644
France	31378	8.2	234
Italy	13411	3.5	100
Japan	87498	23.0	653
UK	26902	7.1	201
US	135587	35.6	1012
Total	381004	100	-

Industry	**Number of patents**	**% share**	**Average micro-sector size**
Chemicals	125788	33	2096
Electronics	154171	40.5	4057
Machinery	101045	26.5	2807
Total	381004	100	-

Table 1 reports the number and distribution of patents in the sample by

[18] This can be found at the following web page: http://www.macalester.edu/research/economics/PAGE/HAVEMAN/Trade.Resources/TradeConcordances.html

applicant's country of residence. It shows that applications by firms in the US and Japan account for almost 60 percent of the sample. Among the European countries, Germany is the one with far the largest number of applications and a share in the sample similar to that of Japan. These shares are similar to the same countries' overall shares at the EPO.

Table 1 also shows the distribution of patents across the three main industries in the sample. Although the number of micro-sectors in the sample belonging to the chemical industry is much higher than the number of micro-sectors in the electronics and in the machinery industries, its share of the total number of patents in the sample is comparable to that of the other two industries, with electronics accounting for the largest share. Indeed, the average size of a micro-sector in the electronics industry (i.e. the total number of applications over the whole sample period) is significantly larger than the average size of a micro-sector in the chemical and machinery industries.

Overall, the distribution of the number of patents in each micro-sector-country pair is very skewed with a predominance of small numbers and very few large numbers, with the latter mostly belonging to the electronics industry and to either Japan or the US. Such a skewed distribution is also typical of the firm level analyses on patents.

The data on citations refers to all the citations to previous European patents (i.e. patents granted by the EPO) reported in the documents of the patent applications in the sample (*backward citations*)[19]. Since each firm in the sample has been identified and has a unique code, I can separate *self* citations (i.e. citations to previous patents held by the applicant firm itself) from all *other*

[19] Since I have backward citations to patents filed at the EPO and there were relatively few EPO applications in the early years there is one further reason to pool the data on citations across time when tracing knowledge flows.

citations. Within these other citations I can then distinguish between citations to patents held by other national firms (*national* citations) and citations to patents held by foreign firms (*international* citations).

Table 2 shows the percentage distribution of national, international and self citations in different industries and countries. 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 once one controls for self citations, the gap being particularly wide in Italy and the UK and, to a lesser extent, in France and Germany. Indeed, self citations represent an important share of overall national citations: this is equal to 35 percent in the whole sample and up to about 50 percent in Italy and in the UK.

Table 2 Percentage share of citations by type

Country(*)	Sector(*)	Citations		
		National(**)	International	Self
All	*All*	0.31	0.51	0.17
	Chemicals	0.29	0.50	0.21
	Electronics	0.35	0.51	0.14
	Machinery	0.28	0.56	0.16
Germany	*All*	0.25	0.56	0.19
	Chemicals	0.22	0.54	0.25
	Electronics	0.23	0.62	0.15
	Machinery	0.32	0.54	0.14
France	*All*	0.18	0.70	0.12
	Chemicals	0.18	0.68	0.14
	Electronics	0.19	0.72	0.09
	Machinery	0.18	0.70	0.12
Italy	*All*	0.13	0.74	0.13
	Chemicals	0.16	0.68	0.16
	Electronics	0.06	0.84	0.09
	Machinery	0.16	0.72	0.12
Japan	*All*	0.38	0.46	0.17
	Chemicals	0.29	0.53	0.18
	Electronics	0.44	0.41	0.15
	Machinery	0.33	0.48	0.19
UK	*All*	0.15	0.68	0.16
	Chemicals	0.18	0.63	0.20
	Electronics	0.12	0.78	0.09
	Machinery	0.14	0.71	0.15
US	*All*	0.39	0.43	0.18
	Chemicals	0.39	0.40	0.21
	Electronics	0.40	0.45	0.14
	Machinery	0.32	0.49	0.18

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

This descriptive evidence is quite striking and does not seem to suggest the existence of significant barriers to knowledge flows across countries, rather the opposite. This is at odds with what Maurseth and Verspagen (2002) have found in a recent paper, and seems even more surprising since they also use European patent citations, although their sample only partially overlaps with mine (it includes a larger set of European countries, but excludes Japan and the US).

One reason for this disagreement could be that Maurseth and Verspagen do not have firm level data: this does not allow them to fully control for self citations, which, as shown in Table 1, account for a significant share of overall national citations. However, they try to mitigate the problem omitting intra-regional citations from the analysis, under the assumption that the majority of self citations should be found within the same region. Although some of the citations that are inter-regional may still refer to intra-firm citations, as the authors explicitly recognise, this methodology might indeed take care of a great deal of the bias self-citations generate.

There is however a second and more important reason that relates to the way the analysis by Maurseth and Verspagen (2002) is designed. They only examine flows between European regions, that is citations from one European region to another European region. In so doing they exclude citations from European regions directed towards Japan and the US, which account for the majority of patent applications at the EPO. This significantly affects the relative weight of national and international citations because a large share of the international citations of patents from European countries are directed towards Japan and the US.

With reference to my sample, this is shown in Table 3, which reports the directions of international citations and their relative weight. Most of the citations are to patents held by firms or institutions in the US, Japan or Germany, with the share of the first two countries ranging from 52 percent (Italy) to 69 percent (Germany). Ignoring citations directed to Japan and the US might then generate a bias in favour of national citations and induce a "border effect", as a consequence of leaving the technological leaders out of the picture[20].

Table 3 Percentage distribution of international citations by country

		Cited country					
		DE	**FR**	**IT**	**JP**	**UK**	**US**
	DE	-	0.12	0.05	0.31	0.14	0.38
	FR	0.28	-	0.03	0.23	0.14	0.32
Citing	**IT**	0.25	0.13	-	0.22	0.10	0.30
country	**JP**	0.27	0.10	0.04	-	0.11	0.49
	UK	0.27	0.12	0.03	0.19	-	0.39
	US	0.28	0.12	0.04	0.39	0.17	-

Note: the percentages in the table refer to the share of citations from the citing country directed towards the cited countries (i.e. row sums are equal to 1).

Table 4 shows the direction of international citations for all the countries in the sample with reference to each of the three main industries. International citations in chemicals and electronics are mostly directed towards the US. In these industries, the intensity of citations flowing towards Germany and Japan is somewhat comparable, while the UK patents appear to be cited more in chemicals than in electronics. Machinery is different in that it is German patents that receive the largest share of international citations from each of the other countries. Regardless of these differences, both Table 3 and Table 4 confirm the role of the US, Japan and Germany as technological leaders.

Having information on the technological class of both the citing and the cited patent, I can also trace patterns of citations across micro-sectors. Although these might be thought as being narrowly defined, still about sixty percent of the citations are found to be directed to other patents classified into the same micro-sector, the percentage being slightly higher in electronics (64 percent) than in

[20] Indeed, in the work by Peri (2003), which does not suffer from this problem, the estimate of the country border effect is significantly smaller than the one found in Maurseth and Verspagen (2002).

chemicals and machinery (56 percent for both)[21].

I should mention that it has elsewhere been noticed that there might exist a potential problem with the informative content of European patent citations. This is related to the number of citations included into the patent document by the examiners, rather than by the innovator: these citations represent knowledge not necessarily known to the innovator, hence not necessarily used in the process leading to the innovation.

This criticism is often raised in the literature and is relevant for both the European and the US patent systems, since in both cases it is patent examiners who finally determine what citations to include into a document. However, while the US system requires applicants to provide a complete description about the state of the art, the European system does not, which implies that the share of citations added by the examiners is likely to be larger in patents filed at the EPO compared to patents filed at the USPTO (Maurseth and Verspagen, 2002, p. 534). While this might increase the noise in the relation between knowledge flows and patent citations in the case of European data, it is not clear that it should lead to any specific bias.

Despite this criticism, there is little existing evidence on the validity of using patent citations as a measure of knowledge flows. A recent paper by Duguet and MacGarvie (2002) assesses the legitimacy of using European patent citations as a measure of knowledge spillovers. They use information from the CIS1 survey collected by the French Service des Statistiques Industrielles, which contains firms' responses to questions about their acquisition and dissemination of new technologies across countries. By matching firms' responses to citation counts

[21] This pattern is consistent across countries, as can be seen in Table 11 in the appendix. Note that the percentage might be higher in electronics because of the larger average micro-sector size within this industry compared to chemicals and machinery industries.

the authors find that patent citations are indeed related to firms' statements about their acquisition of new technology.

Table 4. Percentage distribution of international citations by country within each industry

CHEMICALS

Cited country

		DE	FR	IT	JP	UK	US
	DE	-	0.07	0.03	0.29	0.17	0.45
	FR	0.18	-	0.04	0.21	0.17	0.40
Citing	**IT**	0.19	0.09	-	0.20	0.13	0.39
country	**JP**	0.27	0.06	0.03	-	0.14	0.49
	UK	0.21	0.10	0.03	0.16	-	0.51
	US	0.28	0.10	0.03	0.33	0.25	-

ELECTRONICS

Cited country

		DE	FR	IT	JP	UK	US
	DE	-	0.12	0.03	0.35	0.09	0.40
	FR	0.22	-	0.03	0.28	0.10	0.37
Citing	**IT**	0.19	0.14	-	0.28	0.08	0.32
country	**JP**	0.19	0.10	0.02	-	0.08	0.60
	UK	0.19	0.13	0.02	0.27	-	0.40
	US	0.22	0.12	0.03	0.52	0.11	-

MACHINERY

Cited country

		DE	FR	IT	JP	UK	US
	DE	-	0.16	0.07	0.30	0.14	0.33
	FR	0.37	-	0.03	0.21	0.15	0.25
Citing	**IT**	0.32	0.15	-	0.19	0.10	0.25
country	**JP**	0.40	0.12	0.07	-	0.11	0.30
	UK	0.37	0.15	0.03	0.17	-	0.28
	US	0.37	0.16	0.05	0.27	0.15	-

The results obtained by Duguet and MacGarvie (2002) and the analogous findings of Jaffe, Trajtenberg and Fogarty (2000) on US citations data, strengthen the case for the use of patent citations as they appear to be sufficiently correlated with knowledge flows to allow statistical analysis based on them to be informative about the underlying phenomenon of interest.

Hence, although the data on R&D have some important imperfections, the data on patents and citations are very detailed and have the advantage of including the whole set of EPO patent applications and relative citations for the selected countries and industries. This allows an accurate identification of knowledge flows through citations, on which spillovers measures are based.

Table 5. Summary statistics for the complete sample

Variable	Mean	Std. Dev.	Min	Max
Patents	35.63	67.46	0	1166
RD(*)	2626.97	2842.55	18.90	27113.57
NS(*)	42.68	357.96	0	9106.05
IS(*)	2609.35	1139.75	307.82	7494.91
self	.13	.15	0	1

(*) Units are millions of 1990 US dollars

In the estimation, for all the countries I could not use one of the 135 micro-sectors because no clear correspondence with the R&D classification could be identified. I also dropped from the sample all the micro-sector/country pairs with zero patent counts in each year and further restricted the sample to micro-sectors/country pairs with at least fifteen patents during the sample period in order to avoid jumps due to sporadic observations.

The restrictions to the sample mainly affect the chemical industry, to which most of the micro-sectors with few patent applications belong. Hence, the final sample I use in the estimations includes 712 cross-sectional units, evenly distributed across industries (286 micro-sectors from the chemicals industry, 218 from the electronics industry and 208 from machinery industry). Table **5** reports the summary statistics for the selected sample.

5. Estimation

This section presents empirical methods and results from the estimation of equations (13) and (15).

In the estimation of both specifications the dependent variable is equal to the log of patents for micro-sector *i* in country *h* at time *t*. Since in the sample there are cross-sectional units for which the number of patents is equal to zero in some years and the logarithm of zero is undefined, I add one to all observations of the number of patents and then take the log to obtain the dependent variable used in the log-linear regressions reported below.

Although the above transformation represents the traditional and widely used procedure for dealing with this problem in the literature, there are concerns that it might bias the results. Indeed, as noted in the previous section, the distribution of patents in the sample is highly skewed, with a preponderance of small numbers and a significant percentage of zeros (this is equal to 12 percent in the complete sample). Furthermore, patents are count data and occur in integers. These characteristics are known to generate bias in the estimates of the log-linear model (see Winkelman, pp. 67-8) and motivate the estimation of alternative non-linear models.

Regardless of the model chosen (linear vs. non-linear), a concern in the estimation of both equations (13) and (15) resides in the complex structure of the individual effect, which is characterised by correlation across panels (here: country/micro-sector pairs), hence by a residual variance-covariance matrix that is no longer block-diagonal[22]. If such correlation is ignored, inferences based on OLS or random effects estimation might then be misleading since estimated standard errors are biased downward. By contrast, fixed effects estimates are

[22] This is generated by the data availability problem for R&D through the presence of the spillovers variables, which are built upon it (see footnote 15).

conditional on the individual effects, which leaves the standard errors unaffected[23]. Furthermore, fixed effects methods ensure consistency in the presence of correlation between the explanatory variables and the individual effects. For the above reason, fixed effects methods, although inefficient, are to be preferred.

Before moving to the estimation models and results a final remark should be added with reference to the dependent variable. One might argue that a more appropriate measure of innovation in a field would be the count of patents weighted by the number of citations received (*forward citations*) in order to account for the quality of patents as proxy for new ideas (see Jaffe and Trajtenberg, chapter 2). This would require excluding observations belonging to the last years in the sample, effectively reducing the available period to the 1980's[24]. The benefits of this choice are however uncertain. Using US patent data and citations, Peri (2003) finds no significant difference in the estimates of the effects of R&D spillovers on innovation using weighted and unweighted patent counts. Further, as previously explained, the average quality of the EPO patents in the sample is relatively high, thus adjustment for quality through citations is unlikely to be found more significant in this setting.

The following section briefly describes the non-linear methods employed in the econometric analysis. Subsequent sections comment the empirical results presented

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[23] It should be noted that correlation across panels also occurs when an aggregated variable is included among the regressors (Moulton, 1986). This is the case in both specification (13) and (15), where in each time period there are repeated observations on R&D because the data availability for such variable is limited to a higher level of aggregation than the one used for the dependent variable. The induced correlation problem is here ruled out by assumption (12), which effectively says that having aggregated R&D on the right hand side affects the size of the estimated coefficients, but not the standard errors.

[24] In the NBER data on US patents, Jaffe and colleagues found that the lag distribution of forward citations is skewed to the left, with a mode at about 3.5 years. Most of the citations are received within ten years from granting, but there can be long lags (up to thirty years).

Table 6 through to Table 8.

5.1 Fixed effects non-linear regression models for count data

The basic model found in the literature to handle count data is the Poisson model, which has been extensively used to model patents as a function of R&D (see Hausman, Hall and Griliches, 1984). This model estimates the relationship between the arrival rate of patents and the independent variables. The dependent variable, y_{it}, is assumed to have a Poisson distribution with parameter μ_{it} which, in turn, depends on a set of exogenous variables $\boldsymbol{x}_{it}$ according to the log-linear function:

$$\ln \mu_{it} = \delta_i + \beta \mathbf{x}_{it} \tag{16}$$

where δ_i is the fixed-effect.

One way to estimate this model is to do conventional Poisson regression by maximum likelihood, including dummy variables for all individuals (less one) to directly estimate the fixed effects. If there is no specific interest in the fixed effects or if, as in this case, their number is large conditional maximum likelihood represents an alternative method[25]. Conditioning on the count total for each individual, $\sum_i y_{it}$, it yields a conditional likelihood proportional to

$$\prod_i \prod_t \left(\frac{\exp(\beta \mathbf{x}_{it})}{\sum_s \exp(\beta \mathbf{x}_{is})} \right)^{y_{it}} \tag{17}$$

which no longer includes the δ_i parameters.

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[25] For the Poisson regression the two methods always yield identical estimates for β and the associated covariance matrix (Cameron and Trivedi, 1998), hence the choice of method is entirely dictated by computational convenience.

The fixed effects Poisson regression model allows for unrestricted heterogeneity across individuals, but requires the mean of counts for each individual to be equal to its variance ($E(y_{it}) = V(y_{it}) = \mu_{it}$). This is an undesired feature whenever there is additional heterogeneity not accounted for by the model, i.e. when the data show evidence of overdispersion. Such problem can be dealt with by assuming that y_{it} has a negative binomial distribution (see Hausman, Hall and Griliches, 1984), which can be regarded as a generalisation of the Poisson distribution with an additional parameter allowing the variance to exceed the mean.

In the Hausman, Hall and Griliches (1984) negative binomial model it is assumed that $y_{it} \mid \gamma_{it} \sim \text{Poisson}(\gamma_{it})$ and $\gamma_{it} \mid \theta_i \sim \text{Gamma}(\lambda_{it}, 1/\theta_i)$, where θ_i is the dispersion parameter and $\ln \lambda_{it} = \beta \mathbf{x}_{it}$. This yields the following density function:

$$f(y_{it} \mid \lambda_{it}, \theta_i) = \frac{\Gamma(\lambda_{it} + y_{it})}{\Gamma(\lambda_{it})\Gamma(y_{it} + 1)} \left(\frac{1}{1+\theta_i} \right)^{\lambda_{it}} \left(\frac{\theta_i}{1+\theta_i} \right)^{y_{it}} \qquad (18)$$

where Γ is the gamma function. Looking at the within-group effects only, this specification yields a negative binomial model for the *i*-th individual with

$$\begin{aligned} E(y_{it}) &= \theta_i \lambda_{it} \\ V(y_{it}) &= (1+\theta_i)\theta_i \lambda_{it} \end{aligned} \qquad (19)$$

Under this model the ratio of the variance to the mean (dispersion) is constant within group and equal to $(1+\theta_i)$.

Hausman, Hall and Griliches (1984) further assume that for each individual i the y_{it} are independent over time. This implies that $\sum_t y_{it}$ also has a negative binomial distribution with parameters θ_i and $\sum_t \lambda_{it}$. Conditioning on the sum of counts, the resulting likelihood function for a single individual is

$$\frac{\Gamma\left(\sum_t y_{it}+1\right)\Gamma\left(\sum_t \lambda_{it}\right)}{\Gamma\left(\sum_t y_{it}+\sum_t \lambda_{it}\right)}\prod_t \frac{\Gamma(\lambda_{it}+y_{it})}{\Gamma(\lambda_{it})\Gamma(y_{it}+1)} \tag{20}$$

which is free of the θ_i parameters. The likelihood for the entire sample is then obtained by multiplying all the individual terms like (20) and can be maximised with respect to β the parameters using conventional numerical methods.

Unfortunately, this conditional negative binomial model is not a true fixed-effects method. In a recent paper, Allison and Waterman (2002) have proven that this method does not in fact control for all stable covariates. They argue that the problem originates from the fact that the θ_i parameters that are conditioned out of the likelihood function do not correspond to different intercepts in the log-linear decomposition of λ_{it}.

If we write $\theta_i = \exp(\delta_i)$, equations (19) imply that

$$E(y_{it}) = \exp(\delta_i + \beta \mathbf{x}_{it})$$
$$V(y_{it}) = (1+e^{\delta_i})E(y_{it})$$

from which it appears that the model does allow for an arbitrary intercept δ_i for each individual. However, while changes in $\mathbf{x}_{it}$ affect the mean directly and affect the variance only indirectly through the mean, changes in δ_i affect the variance both indirectly, through the mean, and directly. If δ_i is regarded as representing the effect of omitted explanatory variables, then there is no reason why such variables should have a different kind of effect from that of $\mathbf{x}_{it}$.

Alternatively, starting from (19) suppose that

$$\lambda_{it} = \exp(\delta_i + \beta \mathbf{x}_{it} + \gamma z_i)$$

where δ_i is an individual specific intercept and z_i is a vector of time-invariant covariates. Then conditioning on the total count for each individual does not eliminate δ_i or z_i from the likelihood function[26].

Allison and Waterman (2002) explore alternative methods to control for the δ_i's in the presence of overdispersion. Among the possibilities examined by the authors, a simulation study yields good results from applying the conditional fixed-effects Poisson estimator or, alternatively, an unconditional negative binomial regression estimator (that is assuming that y_{it} has a negative binomial distribution with mean μ_{it} and overdispersion parameter λ) with dummy variables to represent the fixed effects. They show that this last estimator has generally better sampling properties than the fixed effects Poisson estimator and it does not suffer from the incidental parameter bias in the coefficients. However, since it is accompanied by underestimates of the standard errors, these need to be adjusted upward. The downward bias in the standard error estimates can be easily and effectively corrected using a correction factor based on the deviance statistics, where the deviance is defined as

$$D = \sum_i \sum_t \{y_{it} \ln(y_{it} / \mu_{it})\} - (y_{it} + \lambda)\ln[(y_{it} + \lambda)/(\mu_{it} + \lambda)]$$

5.2 Empirical results from the entire sample

Table 6 reports the coefficients and standard errors from the estimation of the basic and extended specification for the entire sample (i.e. all industries and all countries)[27]. Columns labelled FE and RE report results from the fixed-effects

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[26] Symptomatic of this problem is that using statistical packages like Stata and Limdep, which implement (20), one can estimate regression models with both an intercept and time-invariant covariates, which is usually not possible with conditional fixed-effects models.

[27] To allow identification of the own R&D effect, all the models include a dummy variable that controls for those micro-sectors with very few patents that are assigned to industries with high R&D expenditures. This added variable (not reported in the table with estimation

and random effects estimation of the log-linear version of the model; OLS results are reported for comparison in columns one and six. Columns labelled CNB report estimates from the conditional fixed effects negative binomial model proposed by Hausman, Hall and Griliches (1984). Finally, columns labelled UNB report estimates from the unconditional fixed effects negative binomial estimator, with standard errors corrected using the deviance statistics as explained in the previous section[28].

In both the basic and extended specifications the two spillovers variables are always found significant. However, while the size of the international spillover indicator is fairly similar in the different regression models, this is not the case for the inter-sector national spillovers indicator. The difference across specifications suggests that this variable might be (negatively) correlated with the individual effects[29]. This is mainly due to the high serial correlation in the national spillovers variable coupled with its high variability between individuals and gives a further reason for fixed effects estimates to be preferred. Note, however, that if the true flow of national spillovers to a micro-sector is indeed constant in time, then fixed effects estimates might overemphasise the effect of the noise around this value.

Concerns about the ability of the conditional negative binomial estimation to effectively control for the individual effects are confirmed by the result on the

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results) is found to be most effective in OLS estimation, but almost irrelevant in the other models used.

[28] Estimates from the fixed effects Poisson and negative binomial regressions show evidence of overdispersion in the data (the ratio of the deviance to the degrees of freedom is well above one in all cases, whereas for a good fitting model they should be close to 1). Besides, Allison and Waterman (2002) show that the unconditional fixed effects negative binomial estimator is virtually always a better choice than the fixed effects Poisson estimator. For these reasons, estimates from this last regression models are not reported.

[29] Note that the random effects estimation of the same log-linear model delivers estimates close to fixed effects for all coefficients, but the coefficient of *ns* (note however that fixed effects and random effects estimates cannot be directly compared through the Hausman test, since random effects is not efficient in this case).

coefficient of *ns* which, although positive and significant, is closer to the OLS estimate than to the fixed effect one. By contrast, the estimate from the unconditional negative binomial model is remarkably close to the result from fixed effects estimation on the log-linear model. On this basis, the log linear fixed effects and the unconditional negative binomial specifications are to be preferred.

The last five columns of

Table 6 present estimation results for the extended specification. This includes interactions between the spillover indicators and the variable accounting for the incidence of self citations, which is used here as a proxy for firm level research experience in technology related areas.

Coefficients are remarkably stable across regression models[30] and past research efforts appear to be more effective in increasing the elasticity of patents to international spillovers (a simple F test of equality between the two interaction coefficients strongly rejects the null hypothesis). This might be related to the fact that the indicator of international spillovers includes both intra- and inter-sector knowledge flows, while *ns* only accounts for inter-sector knowledge flows. Unfortunately, the data do not allow estimating precisely two separate effects (inter-industry vs. intra-industry) for international spillovers, as that would considerably increase the correlation among some of the explanatory variables.

[30] OLS coefficients are qualitatively comparable, although larger in absolute value.

Table 6. Regression results for the entire sample from the linear and non-linear models

	OLS	FE	RE	CNB	UNB	OLS	FE	RE	CNB	UNB
rd	0.18 (.06)	0.18 (.02)	0.27 (.02)	0.20 (.01)	0.18 (.02)	0.18 (.06)	0.18 (.02)	0.26 (.02)	0.20 (.01)	0.18 (.02)
ns	-0.03 (.01)	0.31 (.04)	-0.02 (.01)	0.06 (.01)	0.34 (.04)	-0.04 (.01)	0.27 (.04)	-0.02 (.006)	0.05 (.01)	0.32 (.04)
is	0.26 (.12)	0.24 (.03)	0.25 (.03)	0.30 (.03)	0.26 (.03)	0.21 (.12)	0.22 (.03)	0.23 (.03)	0.29 (.03)	0.26 (.03)
*ns*self*						0.13 (.03)	0.02 (.01)	0.03 (.006)	0.03 (.01)	0.02 (.01)
*is*self*						0.22 (.04)	0.07 (.01)	0.07 (.008)	0.05 (.01)	0.07 (.01)
self						-1.60 (.36)	-0.46 (.09)	-0.52 (.09)	-0.46 (.12)	-0.47 (.13)
time effect	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
country effects	yes	n.a.	yes	yes	yes	yes	n.a.	yes	yes	yes
industry effects	yes	n.a.	yes	yes	yes	yes	n.a.	yes	yes	yes
LnLik				-30296	-33368				-30217	-33278
Obs.					10680					

Note: Columns labelled OLS, FE (fixed effects) and RE (random effects) report estimates of the linear model, where the dependent variable is ln(patents+1). Finally, columns labelled CNB and UNB report estimates from the conditional and unconditional negative binomial models, respectively. Estimates from the unconditional negative binomial model are obtained adding dummy variables to represent the individual effects (not reported). Standard errors are in parentheses. OLS standard errors are robust to heteroskedasticity and correlation within panels: both these and RE standard errors might be biased downwards as they do not account for the correlation across individual effects. FE and UNB standard errors are instead reliable. The latter are corrected using the deviance statistics.

These results show that international spillovers play an important role in explaining innovative productivity: in the preferred specifications, their coefficient is always positive and comparable to that of national spillovers and of own R&D. The estimation results also provide evidence of a positive effect of past research effort on the ability to understand and exploit external knowledge, that is of a significant role of absorptive capacity in increasing innovative productivity. Indeed, the estimated overall elasticity of patents to absorptive capacity from the fixed effects linear model is equal to 0.16. Because the coefficients on the interaction terms are multiplied by λ and are always positive, if anything this result underestimates the true elasticity of patents to absorptive capacity. Note, however, that its effect is comparable to the effect of own R&D.

5.3 Empirical results at the industry level

In the regressions on the entire sample industry dummies are found significant: this provides a first coarse indication of the existence of relevant differences across industries. In order to gain a more complete understanding on this issue, Table 7 presents results from industry level regressions.

Micro-sectors within the chemical industry display a high elasticity to own R&D compared to micro-sectors in the electronics and machinery industries. Inter-sector national spillovers are never found effective in increasing innovation independently of absorptive capacity in the chemical industry, while in the electronics industry their impact is stronger than that of own R&D[31]. Finally, the elasticity of patents to international spillovers is always positive and significant and it is not statistically different from that to own R&D: a test of equality between the coefficients of *rd* and *is* cannot reject the null in each of the three samples.

These estimates show that, with the exception of chemicals, national and international spillovers are together more effective than own R&D in increasing innovative performance. However, their relative importance is different in the three industries: international spillovers are respectively more, equally and less effective than national spillovers in the chemicals, machinery and electronics

[31] A test of equality between the coefficients of *rd* and *ns* rejects the null at the 5 percent confidence level.

industry[32], as summarised in Figure 1.

Table 7. Regression results at the industry level from the linear and non-linear models

	CHEMICALS			ELECTRONICS			MACHINERY		
	FE	**CNB**	**UNB**	**FE**	**CNB**	**UNB**	**FE**	**CNB**	**UNB**
rd	0.41	0.46	0.46	0.12	0.11	0.13	0.21	0.17	0.17
	(.05)	(.04)	(.06)	(.03)	(.02)	(.04)	(.03)	(.02)	(.03)
ns	0.06	-0.01	0.14	0.32	0.07	0.24	0.13	0.10	0.28
	(.07)	(.01)	(.09)	(.06)	(.01)	(.08)	(.05)	(.02)	(.05)
is	0.35	0.38	0.33	0.14	0.21	0.14	0.14	0.25	0.19
	(.07)	(.05)	(.06)	(.05)	(.04)	(.05)	(.06)	(.05)	(.05)
*ns*self*	0.04	0.04	0.03	-0.004	0.01	-0.002	0.006	0.02	-0.003
	(.01)	(.01)	(.01)	(.02)	(.02)	(.03)	(.01)	(.02)	(.02)
*is*self*	0.09	0.09	0.10	0.09	0.06	0.08	0.04	0.04	0.05
	(.01)	(.01)	(.01)	(.02)	(.02)	(.03)	(.02)	(.02)	(.02)
self	-0.82	-0.91	-0.93	-0.69	-0.59	-0.65	-0.21	-0.35	-0.27
	(.14)	(.17)	(.20)	(.21)	(.26)	(.33)	(.18)	(.27)	(.27)
time effect	yes	yes	yes	yes	yes	yes	yes	yes	yes
logLik		-11571	-12742		-9751	-10748		-8783	-9692
Obs.	4290	4290	4290	3270	3270	3270	3120	3120	3120

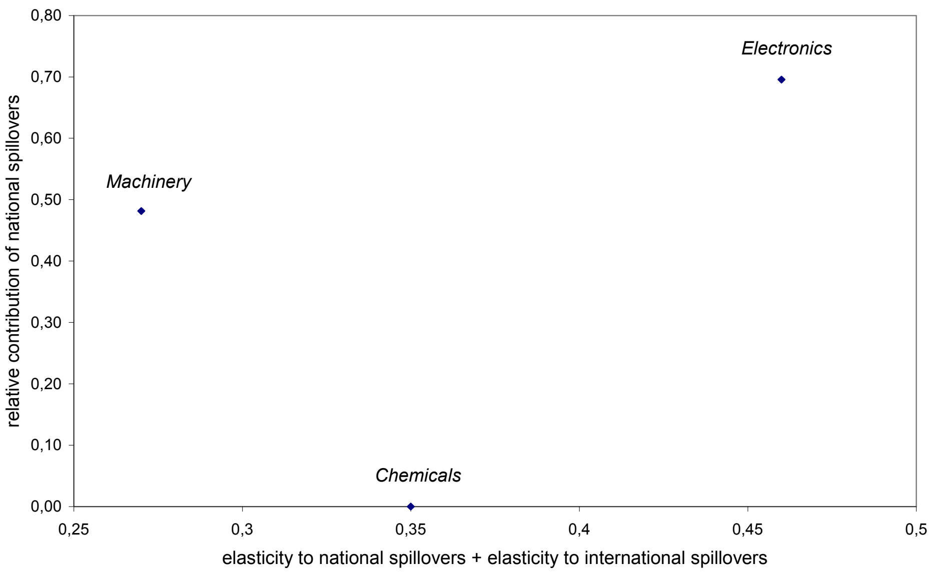
Note:See

[32] Although in the machinery sample the point estimate of the coefficient of *ns* from the unconditional negative binomial model appears larger than the estimate of the coefficient of *is*, the difference is not statistically significant.

Table 6.

With reference to absorptive capacity, the results show that it is effective in rising the elasticity of patents to international spillovers in all industries. The overall elasticity of patents to absorptive capacity obtained from the estimated linear model and calculated around the means of the variables is equal to 0.27 in chemicals, 0.13 in electronics and 0.09 in machinery. Hence own past experience in technology related fields seems to be particularly important in the chemicals industry, where a unit increase in the indicator of experience would generate 45 more patents in the current year at the mean of the variables. This is almost the double of the average number of patents in the chemicals sample. A unit increase in the indicator of experience would instead generate 59 more patents in the electronic industry (1.3 times the average) and 29 more patents in the machinery industry (about the average number of patents in the industry).

Figure 1. Relative importance of national and international spillovers in the three industries



<u>5.4 Leaders vs. "followers"</u>

Looking both at the volume of patent applications (Table 1) and at the direction of patent citations (Table 3) it is clear that US, Japan and Germany have the role of technological leaders and that France, the UK and Italy, although definitely among the most advanced countries, are somewhat lagging behind. Based on this observation, I split the sample in two groups, leaders (US, Japan and Germany) vs. “followers” (France, UK and Italy), and perform separate estimations on the two samples.

Table 8. Regression results for different groups of countries

	Leaders			"Followers"		
	FE	**CNB**	**UNB**	**FE**	**CNB**	**UNB**
rd	0.24	0.24	0.23	0.17	0.13	0.13
	(.03)	(.02)	(.03)	(.03)	(.03)	(.03)
ns	0.24	0.06	0.30	0.15	0.04	0.21
	(.05)	(.01)	(.06)	(.05)	(.01)	(.05)
is	0.23	0.31	0.25	0.32	0.46	0.47
	(.04)	(.03)	(.03)	(.07)	(.06)	(.06)
*ns*self*	0.02	0.02	0.001	0.02	0.04	0.03
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
*is*self*	0.07	0.03	0.05	0.07	0.06	0.07
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
self	-0.29	-0.07	-0.03	-0.55	-0.72	-0.71
	(.12)	(.16)	(.22)	(.13)	(.17)	(.17)
time effect	yes	yes	yes	yes	yes	yes
country effects	n.a.	yes	yes	n.a.	yes	yes
industry effects	n.a.	yes	yes	n.a.	yes	yes
lnLik		-18121	-19934		-12064	-13320
Obs.	5685	5685	5685	4995	4995	4995

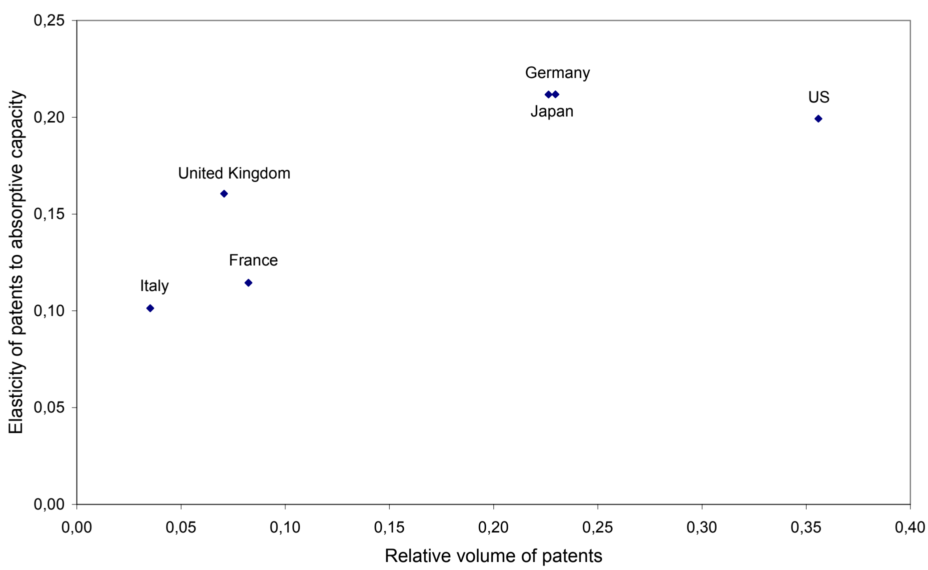
Note:See

Table 6.

The main interest here lies in assessing whether absorptive capacity has a different effect in the two groups. From the theoretical point of view, absorptive capacity can be thought of having a non-linear effect. The farther a firm/country is from the technological frontier (i.e. the larger the gap with the technological leaders), the lower is its ability to absorb and exploit new external knowledge (mostly produced from the technological leaders). However, the farther a country is from the technological frontier, the larger is its potential to increase this ability (Griffith et al, 2000).

We would then expect to find a stronger overall elasticity of innovation (patents) to absorptive capacity in the group of technological leaders, compared to the "followers" (prediction 1). We would also expect the elasticity to absorptive capacity to increase less then proportionally as we move towards the technological frontier (prediction 2).

Figure 2. Elasticity of patents to absorptive capacity



Note. The relative volume of patents is calculated with reference to the six countries total volume over the whole sample period.

The estimation results for the two groups of countries are presented in Table 8.

Technological leaders display elasticities to national and international spillovers similar to that of own R&D, while "followers" benefit more from international spillovers than from own research efforts (although the difference is significant only at the 10 percent confidence level).

In line with our expectations, the overall elasticity of patents to absorptive capacity is estimated to be 0.21 for leaders and 0.13 for "followers": a unit increase in the indicator of absorptive capacity at the means of the variables originates an increase in the number of patents equal to 76 in the technological leaders and to 17 in the "followers". In Figure 2, estimates of the elasticity of patents to absorptive capacity (calculated separately for each country in the sample) are plotted against the countries' relative volume of patents (a very coarse proxy for the world technological frontier). The resulting pattern appears increasing, thus in line with prediction 1. However the number of countries is too small to allow any clear inference on prediction 2, but note that the results are not inconsistent with the corresponding claim: the pattern also appears to increase at a declining rate, thus suggesting that a unit movement towards the technological frontier has a larger impact on the ability to absorb and exploit external knowledge the farther from the frontier itself is the country's initial position.

6. Conclusions

This paper provides an empirical assessment of the effect of national and international knowledge spillovers on innovation at a finely defined sectoral level for six major industrialised countries over the period 1981-1995. Despite some data limitations, the results presented give evidence of the importance of such spillovers and of their different impact in different industries.

The measures of knowledge spillovers are built using citations included in patent applications at the European Patent Office. Once self-citations are controlled for, citation patterns do not show any home country bias. A large share of the total number of citations by patent applications from (firms within) a country are to foreign patents (international citations), the share being larger for countries behind the technological frontier. Consistently, international spillovers are always found to be effective in increasing innovative productivity.

The paper then investigated the role of prior R&D experience in enhancing a country's ability to understand and improve upon external knowledge. This *absorptive capacity* is measured using self-citations, which are a signal of knowledge accumulation within the firm. The empirical results show that absorptive capacity increases the elasticity of a country's innovation to both national and international spillovers. Its effect is non-linear: the larger the gap of a country with the technological leaders the weaker is the country's ability to absorb and exploit external knowledge, but the larger is its potential to increase such ability.

Appendix

Table 9. The list of micro-sectors

CHEMICALS:	
1) chem11	Technical polymers
2) chem12	Thermoplastics
3) chem13	Polyacetale
4) chem14	Artificial and natural caoutchouc
5) chem15	Natural polymers
6) chem16	Plastic trash
7) chem17	Plastic products
8) chem21	Inorganic chemical compounds
9) chem22	Inorganic oxygen compounds
10) chem23	Inorganic sulphide compounds
11) chem24	Other metal salts
12) chem25	Other inorganic chemical products
13) chem26	Radioactive substances

14) chem31	Synthetic textile fibres
15) chem32	Artificial textile fibres
16) chem33	Trash
17) chem41	Organic oils and fats
18) chem42	Wax
19) chem43	Artificial wax
20) chem44	Chemical products of wood or resins
21) chem51	Hydrocarbons
22) chem52	Alcohol
23) chem53	Carbon acid
24) chem54	Compounds with nitrogen function
25) chem55	Organic-inorganic compounds
26) chem56	Lactam, other heterocyclic compounds
27) chem57	Sulphamide
28) chem58	Ether, alcohol peroxide
29) chem61	Synthetic organic colours and varnishes
30) chem62	Tanning agents and paint extracts
31) chem63	Colours, varnishes, pigments
32) chem64	Glazes, sealing compounds
33) chem71	Vitamins, provitamins, antibiotics
34) chem72	Hormones and derivatives
35) chem73	Micro-organisms, vaccines
36) chem74	Reagents and diagnostics
37) chem75	Other special medicines
38) chem76	Other pharmaceutical products
39) chem77	Cosmetics (no soaps)
40) chem81	Etheric oils and perfumes
41) chem82	Soaps
42) chem83	Detergents
43) chem84	Ski-wax, furniture polishes
44) chem91	Fertilisers
45) chem92	Insecticides
46) chem101	Starch
47) chem102	Proteins

48) chem111	Explosives, gunpowder
49) chem112	Fuses, ignition chemicals
50) chem113	Pyrotechnic articles, fireworks
51) chem114	Matches
52) chem121	Additives for lubricating oil, corrosion inhibitors
53) chem122	Liquids for hydraulic brakes, anti-freezing compounds
54) chem123	Lubricants, emulsions for grease, artificial graphite emulsion
55) chem131	Gas cleansing
56) chem132	Catalysts
57) chem133	Additives for metals
58) chem134	Benzol, naphtha
59) chem135	Electronic and electro-technical chemical compounds
60) chem136	Chemical substances for constructions
61) chem137	Chemicals for fire extinguishers, liquid polychlor diphenyle
ELECTRONICS:	
1) elek10	Ignition cables, electrical cars
2) elek11	Small electrical engines, electrodes
3) elek11b	Portable electrical tools
4) elek12	Motors, electrical engines and electrodes
5) elek12b	Magnetic tapes
6) elek13	Choke coils, converters, transformers
7) elek13b	Traffic lights, etc.
8) elek14	Generators and equipment
9) elek14b	Particles accelerator
10) elek15	Transformers
11) elek15b	Lasers
12) elek21	Fridges (for home and industry), air conditioning
13) elek22	Washing machines, dryers, dish washers
14) elek23	Electrical shavers, hair-cutting machines, hoovers
15) elek24	Electric heating
16) elek31	Computers and equipments

17) elek32	Computer chips and equipments
18) elek33	Photocopying machines and equipments
19) elek34	Type-writers and other office devices
20) elek41	TV, radio, TV-cameras, video-cameras, antennas, oscilloscopes
21) elek42	Microphones, loud-speakers, recorders
22) elek43	Telephones (no mobile phones)
23) elek44	Radio engineering devices
24) elek511	Circuits
25) elek512	Resistors
26) elek513	Switches, fuses
27) elek514	Control panels
28) elek521	Cables (without ignition)
29) elek522	Insulators
30) elek53	Capacitors
31) elek54	Electro-magnets
32) elek61	Electrical diagnostic devices (no X-rays)
33) elek62	X-rays
34) elek63	Instruments to show ionic beams
35) elek71	Diodes, transistors
36) elek72	Integrated circuits
37) elek8	Batteries, accumulators
38) elek9	Portable electrical lamps
MACHINERY:	
1) masch10	Printing machines
2) masch11	Steam-boiler
3) masch11b	Machines for food processing
4) masch121	Steam-turbines for ships
5) masch122	Steam-turbines for steam power plants
6) masch12b	Machines to process rocks, etc.
7) masch131	Gas-turbines for aeroplanes
8) masch132	Gas-turbines for power stations
9) masch13b	Wood processing machines

10) masch14	Plastic processing
11) masch15	Cutting machine tools (saws, etc.)
12) masch16	Non cutting machine tools
13) masch17	Metal-working rolling mills
14) masch18	Soldering irons, blow lamps, welders
15) masch19	Torches, furnaces
16) masch20	Ovens, distilling apparatuses, gas distilling
17) masch21	Piston-drive engines for aeroplanes
18) masch21b	Pumps, centrifuges, filters
19) masch22	Engines for cars
20) masch22b	Conveyors
21) masch23	Engines for ships
22) masch23b	Anti-friction bearing
23) masch24	Engines for trains
24) masch24b	Valves
25) masch25	Packaging machines
26) masch26	Scales
27) masch27	Fire extinguisher, spray guns
28) masch28	Other machines
29) masch3	Water-turbines
30) masch4	Nuclear power reactors
31) masch5	Other engines
32) masch61	Agricultural machines (without tractors)
33) masch62	Tractors
34) masch7	Constructions and mining machines
35) masch8	Textile machines
36) masch9	Paper production machines

Table 10. 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 micro-sectors employed in the analysis belong to the sectors whose rows have been evidenced. In only one case (one electronics micro-sector in the UK) we have used R&D data for "Paper, Paper Products & Printing".

Table 11. Relative share of number of citations per patent within (intra-class) and outside (inter-class) the micro-sector of the citing patent.

Country(*)	**Sector(*)**	**Intra-class**	**Inter-class**
All	*All*	0.59	0.41
	Chemicals	0.56	0.44
	Electronics	0.64	0.36
	Machinery	0.56	0.44
Germany	*All*	0.58	0.42
	Chemicals	0.56	0.44
	Electronics	0.63	0.37
	Machinery	0.56	0.44
France	*All*	0.59	0.41
	Chemicals	0.55	0.45
	Electronics	0.64	0.36
	Machinery	0.56	0.44
Italy	*All*	0.60	0.40
	Chemicals	0.57	0.43
	Electronics	0.63	0.37
	Machinery	0.60	0.40
Japan	*All*	0.59	0.41
	Chemicals	0.55	0.45
	Electronics	0.62	0.38
	Machinery	0.53	0.47
UK	*All*	0.57	0.43
	Chemicals	0.54	0.46
	Electronics	0.63	0.37
	Machinery	0.56	0.44
US	*All*	0.61	0.39
	Chemicals	0.57	0.43
	Electronics	0.66	0.34
	Machinery	0.58	0.42

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

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