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ANALYSIS OF R&D SPILLOVER EFFECTS ON LARGE INTERNATIONAL FIRMS' ECONOMIC PERFORMANCE.

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CONTENTS.

Introduction.

The aim of this research[1] is to assess the magnitude of R&D spillover effects on large international companies' productivity growth. In particular, we investigate the extent to which R&D spillover effects are intensified by both geographic and technological proximities between spillover generating and receiving firms.

To this end, we use three different methodologies to construct the stock of R&D spillovers: i) technological proximity; ii) geographic distance; and iii) patent citations based proximity.

The approach for modelling technology based R&D spillovers builds on the methodology first empirically implemented by Jaffe (1986). This method rests on technological proximities between firms in a technological space. The firms' positions in the technological space are characterized by the distribution of their patents over patent classes.

Locational R&D spillovers rest on the geographical distances between firms which uses the latitude and longitude coordinates of corporate headquarters (Orlando, 2000). Firms falling inside a circle around the geographic centroid of the firm's location are defined as geographically near.

Then, we construct a new measure of proximity based on the patent citation data, without imposing symmetry.

Finally, following Mancusi (2004), self-citations to firms patents are used to measure the level of knowledge accumulation internal to the firm and the

[1] I would like to thank my supervisor, Prof. Alfredo Del Monte (University of Naples Federico II), and Prof. Michele Cincera (Université Libre de Bruxelles) for their useful comments and suggestions.

importance of absorptive capacity in enhancing the ability to benefit from geographic and technology based R&D spillovers.

An extended production function (Griliches, 1979) is used to estimate the impact of R&D spillover components and absorptive capacity besides the traditional inputs and own R&D stock.

The dataset consists of a representative sample composed of 964 worldwide R&D-intensive manufacturing firms over the period 1988-1997. This information is matched to the USPTO dataset of Hall, Jaffe and Trajtenberg (2001).

The work is organised as follows. In chapter 1, we provide some useful definitions about the technological change. In chapter 2, we illustrate the theoretic and empirical literature about the R&D spillover effects and firms' ability to identify, assimilate and exploit external knowledge (absorptive capacity). In chapters 3, 4, 5 we describe the dataset and we implement three different methodologies to construct the stock of R&D spillovers: technology based approach, geography based approach and patent citations based approach.

Finally, a concluding chapter summarises the empirical findings and points out some directions for future research.

1. Technological change: definitions and characteristics.

1.1 Concepts and definitions

Research and Development (R&D) activities represent the most privileged method by which companies generate and acquire technological information.

According to Stoneman (1983), the concept of technological change encompasses improvements in products, production processes, material and intermediate inputs, and management methods in the economic system. The notion of change of techniques is close to the one of technological change. However, the distinction between these two notions appears to be ambiguous and imprecise and authors often indifferently use either one or the other. Mansfield (1968) defines technology as a whole set of (technical or managerial) knowledge which enables to launch new products or processes. Techniques differ from technology in so far as, the former is a production method at a given time which is defined by the equipment and management methods used, while the latter encompasses the whole set of knowledge used in the production. The term 'technique' can be reserved for productive equipment and the work organization they involve. Technology is a more comprehensive concept that incorporates other functions such as management and control which are grafted on to the technique.

Following the schumpeterian thought, it is common to divide the technological change process into three stages: invention, innovation, diffusion.

The first stage, the ***invention process***, corresponds to the generation of new ideas, e.g. new product, process or system. The inventing activity encompasses not only the creation (thanks to the use of existing and new knowledge) of previously non-existent products, processes and systems, but also an original exploitation of elements that have always existed.

The ***innovation process*** is the second stage of technological change. During this stage, new ideas are developed into marketable products and processes. Schumpeter (1942) distinguishes five main types of innovation: product innovation, process innovation, new markets and marketing methods, legislation changes, and innovations with regard to organization. ***Product innovation*** relates to R&D aimed at improving, creating, introducing or diffusing new products (with the production process being unchanged) while ***process innovation*** is referred to as R&D activities directed towards perfecting the methods or obtaining new processes. Process innovations generally reduce the cost of producing a generally unchanged product. However, both kinds of innovations very often go hand-by-hand.

During the final ***diffusion*** stage, new products and processes spread across the potential market. According to Vickery and Blair (1987), the speed at which new technologies diffuse and are applied in the manufacturing industry as well as the direction in which this process propagates, play a determining role in economic growth and competitiveness. Among the factors that influence the diffusion process, one has to distinguish between macro and micro economic factors. At the macro level, the global domand, the level of prices, the level of competitiveness, the balance of payments (to the extent that it favors export), employment and the global behavior of the labor markets are the key determinants that are likely to induce the diffusion of technologies. Among the factors at micro level, the authors bring to the fore the sectorial distribution of firms, their size, their sensibility to new technologies, the existence of a skilled personnel, the technical problems raised by applying new technologies, the sources and the cost of financing it, the environment and technological infrastructure. In addition to the market structure, the speed at which the diffusion process occurs is likely to vary according to whether a new technology spreads across firms beloging to different industries (inter-industry diffusion) or firms within the same industrial sector (intra-industry diffusion). The same distinction can be made for firms in different countries (international diffusion) or located within the boundaries of any given country (intra-national diffusion).

The diffusion process is closely linked to the time profile of technological change and new technologies usually take a considerable time to diffuse. This argument introduces the notion of generic (or drastic) versus minor (or incremental) innovations. An ***incremental innovation*** refers to the small and continuous improvements and/or further developments which follow a major or ***drastic innovation***.

Another common distinction regarding technological innovation is the one between global and local innovations. A ***global innovation*** is often referred to as being the first occurrence in an economy (launching a new product for instance), while a ***local innovation*** is also concerned with the introduction of a new innovation but in the unit of observation, e.g. a firm.

Finally, it should be noted that the threefold process of technological change is not linear. Each stage is characterized by a selection process: only certain new ideas are developed through the market and only some of innovations are successfully diffused. Moreover, there are extensive feedbacks from one stage to the other and it is hard to adequately represent the whole process of technological change by a linear process. These feedbacks effects have to be considered when characterizing of time profile of technological change.

Research and Development (R&D) is commonly thought as being the main source of technological change. R&D is usually organized in three activities: fundamental research, applied research and development.

Fundamental research consists in experimental or theoretical works aimed at acquiring further knowledge about the foundations of observable phenomena and facts, without considering any particular application or utilization. The expected result is discovery. Fundamental research comes close to the notion of ***basic research*** which can be defined as research activities undertaken with no particular applied objective in view. Hence, most scientific research activities as well as the research performed by universities or public institutes are considered as basic research. In terms of the three stages of technological change process, basic research would be more related to the invention stage.

Applied research also consistes in experimental works which are mainly undertaken to acquire further knowledge. However, applied research departs from fundamental research in so far as the former is directed towards a specific objective or particular goal. Applied research is more likely to take place in the commercial sector and it corresponds to the innovation stage of technological stage.

Development is concerned with systematic work based on existent knowledge obtained through research and/or practical experience with a view of:

- Launching the production of new materials, products or devices.
- Establishing new processes systems or services, or,
- Improving those that already exist.

The expected result is information and innovation through investment and experience. Finally, in order to bring out the strategic elements associated with research activities, both basic or fundamental and applied research can be split into subcategories: pure and oriented fundamental research, on the one hand, and general oriented and specific applied research, on the other hand.

Pure fundamental research is carried out with the view of making knowledge process without working for long-term economic or social benefits, with no deliberate efforts being made to apply the outcomes of this research towards practical issues, or for transferring the results towards sectors in charge of their application. ***Oriented fundamental research*** is undertaken with the hope that it will result in setting up a large knowledge base allowing to solve problems or to give concrete expression to current or future opportunities. ***General oriented***

applied research consists in original works undertaken with the view of acquiring new knowledge which has not yet reached the phase in which it is possible to define what would be *in fine* its application or practical determined objective. ***Specific applied research*** is referred to as original works undertaken in order to acquire new knowledge centered on a determined goal or practical objective whose applications are clearly and already known.

1.2 Inefficiencies of knowledge generating activities.

One fundamental charactestic that differentiates R&D activites from other economic activities is the uncertainty and risks inherent to it. These uncertainties play a fundamental role in the allocation of resources to innovate. Arrow (1962) showed why the three generic sources of possible failure of perfect competition (indivisibilities, uncertainties, externalities) to achieve Pareto-optimality in resource allocation, hold in the case of knowledge generating activities.

First, because of time it takes to succeed, a typical R&D project involves important fixed set-up costs. Hence R&D activities should be viewed mainly as a fixed factor of production and consequently, they require economies of scale to be written off the original costs. The ***indivisible*** aspect of R&D as an input causes non-convexities in the production functions and imply that the marginal costs are under the average costs, a situation which is not viable under perfect competition. Second, R&D activities are inherently risky. These technological ***incertainties*** add to the commercial risk of successfully selling a product on the final market of goods and services and lead firms to choose to produce or invest too-little in R&D

activities. Moreover, beside the pure technological difficulty of any R&D project, its probability to succeed also depends on the amount of effort undertaken by researchers which is difficult if not impossible to perceive. This raises a moral hazard issue since agents mostly are unable to shift the risks intrinsic to R&D projects. Third, the public goods feature of knowledge generates ***externalities*** or ***technological spillovers***. The theory of optimal resource allocation under the presence of externalities has been studied through the divergence between the social and private returns (or costs) of production process. In the case of knowledge, this wedge arises because of the non rival and partially excludable property of knowledge which distinguishes it from other strategic activities undertaken by firms. Non rivalry means that the use of an innovation by an agent does not preclude others to use it, while partially excludability implies that the owner of an innovation cannot impede others to benefit from it free of charge. Because of this, the rate of return from an innovation is lesser and as a result, the incentives for carrying out R&D are reduced.

It has just been argued that, because of partial public aspect of knowledge, firms that undertake technological activities does not exclude others from obtaining a part of benefits free of charge. Hence, these externalities or technological spillovers occur because the benefits derived from R&D activities are not entirely appropriable. Actually, as stressed by Griliches (1979), there is often a confusion about two distinct notions of technological spillovers. The first kind of spillovers is related to new products or processes which embody technological change and are bought by other firms at less their full quality adjusted prices. The second kind of technological spillovers can be defined as the potential benefits of the research activity of other firms for a given firm. As pointed out by Gerosky (1995), knowledge spillovers are basically externalities that flow between 'adjacent' producers and/or users of an innovation. To measure their size, one needs to decide which producers or users are 'adjacent' to each other. Hence, a distinction can be made between the spillovers emanating from the firm's industry and those generated by other industries. According to the firm's country of origin, a similar distinction can be made between the national and international nature of these spillovers.

In order to assess the impact and the size of technological spillovers, one needs to focus on some observable measures of performance which are likely to be affected by such phenomena. One of these variables are the costs required to undertaken an innovation. Indeed, if the appropriability of knowledge is imperfect and if many firms are involved in similar technological activities, then the costs of an innovation for a given firm are likey to be affected by these activities. For instance, if the technological spillovers and the firm's own R&D are complementary, then an increase of these spillovers should lead the firm to intensify its R&D effort. In turn, this intensification of the R&D effort should be reflected in the number of patents the firms applies for. Another variable likely to be affected is total factor productivity. If productivity performances are associated with investment in the improvement of technology, then these improvements should be affected not only by the firm's own R&D activities but also by the pool of general knowledge accessible to it. In other words, the R&D activities that spill over to a firm affect its productivity performances. Also, if R&D intensive inputs are purchased from other firms at less their full quality adjusted price, then these quality improvements, to the extent that they are imperfectly, if at all, incorporated in official prices indexes, should be translated into lower productivity effects.

Finally, it should be noted that because of lags in the diffusion of knowledge, spillover effects are probably not contemporaneous. That is, the time it takes for these effects to concretize into new products and processes and result in productivity performance, may actually be quite long.

If flows of knowledge among producers and users of innovation are observed in the economy, then the outcomes of R&D activities are not entirely appropriable. This appropriability issue arises when the costs of transmitting technology are not very high. Several factors can be expected to affect these costs: the nature of technology, its rate of change, and the degree to which it is related to the firm and experience, the legal and institutional characteristics of markets, the internal capabilities of the innovator.

1.3 Technological competition.

The main argument put forward by the equilibrium models of market structure is the fact that the smaller the number of firms in an industry, the more influence those firms have over prices and the less efficient they will be in terms of output. Schumpeter (1942) showed that a theory including innovations leads to different conclusions from those of equilibrium models. Schumpeter argues that for firms engaged in innovative activities, conditions of imperfect competition can sometimes be necessary and more efficient than perfect competition, especially in the long-run. Following this assertion, two hypotheses can be intensively investigated in the literature: innovation increases more than proportionally with the firm size, and innovation increases with the market size.

Several arguments for a positive effect of firm size on innovation have been suggested. First, imperfections associated with capital markets give an advantage to large firms in securing finance for risky R&D projects to the extent that the availability and stability of internally generated funds are higher. Second, to the extent that the economies of scale and scope are important in R&D activities, the returns from R&D will be higher for large and diversified firms. For instance, large volume of sales and complementaries between R&D and other manufacturing activities allow to further spread the fixed costs of innovation. Still, counter-argument to firm size have been put forward. The first one is the loss of managerial control or conversely the excess of the bureaucratic control associated with the firm size. A second counter-argument is the lesser incentives of the R&D personnel because of the lesser appropriability of individual effort and frustration of hierarchies.

Regarding the effects of market concentration on innovation, Schumpeter advances three arguments. First, the incentive to invent is associated with expected ex-post market power. Second, ex-ante market power reduces the uncertainty associated with excessive rivalry and third, the profits generated by ex-ante market power provide internal financial resource which can be allocated to innovative activities without calling on outside financing.

Beside firm size and market power, other relevent firm's characteristics explaining the incentive to undertake R&D have been examined in the literature. One of these characteristics is the firm's cash flow which represents a measure of a firm internal financial capability. The main reason for examining cash flows as a determinant of R&D effort is based largely on the argument that in a world of capital market imperfections, large firms are favored by available internal funds.

Another firm characteristic which has often been investigated is the diversity of the firm's activities. This determinant finds its origin in Nelson's argument (1959) according to which, the unpredictable nature of the results of research activities implies that the diversified firm possesses more opportunities for exploiting the new knowledge or is better positioned to exploit complementarities between its various activities.

The last factor explaining the level of effort devoted by firms to innovative activities is their specific capabilities to link product development and upstream applied research. Such capabilities are associated with the firm's internal organization and information processing as well as the composition and the nature of R&D.

In addition to these firm's specific characteristics, three kinds of conditions that affect interindustry variations in innovative acitivity and performance have been identified. These conditions are: the demand an innovator faces in the market of final goods, the technological opportunity and the conditions in appropriating the results of his innovations. These conditions are more likely to differ across industries and technological areas of research activities and be more or less constant within a given industry.

Schmookler (1954, 1966) have emphasized the role of 'demand pull' forces behind technological change. These determinants correspond to the market factors attracting and influencing innovation. According to Schmookler, the rate and direction of technological change is the outcome of profit seeking firms and as a consequence of the demand. Among the main different interindustry differences of demand conditions which affect the incentives to engage in innovative activities, a distinction can be made between the size of the market goods, and the price elasticity of demand. Hence, for Kamien and Schwartz (1970), the gains from reducing the costs of production, in the case of a process innovation, are larger the more elastic the demand is. On the contrary, according to Spence (1975), the gains from improvements in product quality, in the case of product innovation, are larger the more inelastic the demand is (inelastic demand tends to magnify the gains from a rightward shift in the demand curve). It should be noted that the overall effect of price elasticity is ambiguous since, very often, no distinction is made between product and process R&D.

Rather than as exogenous, the market structure and the conditions characterizing it should be viewed as an evolutionary process. For example, the launch of a new innovation in an industry is likely to have some kind of ripercussion on the firms' behavior. For instance, a firm adopting an innovation which consists of a semiprocessed product will reallocate its inputs. Also, because of this adoption, the profits, the market share and the price of the final good are likely to vary. These changes will be transmitted to the firm's upstream suppliers, as well as to its downstream customers. The demand of the new good may intensify to the detriment of the previous inputs because of their lesser efficiency or even because of their obsolescence. The launching of a new drastic innovation in an industrial sector often leads to the development of several innovations of lesser importance. The reasons which motivate the development of such incremental innovations may be the consequence of new needs from the consumers generated by the generic innovation.

It would be a truism to say that technical advance, at prevailing input prices, is easier, i.e. less costly in some industries than in others. These difficulties or costs associated with the innovative activity in any field of technological specialization can be apprehended under the notion of technological opportunity. Two main reasons can be put forward to explain why these costs may vary according to technological fields: the characteristics intrinsic to technology, and the available stock of scientific knowledge at a certain point of time. Both differ across fields of technological specializations. Because of these characteristics, it might be more difficult for instance, to make a drastic discovery in the field of thermonuclear fusion than in the field related to the aerodynamique shape of motor vehicles. These differences are assumed to be reflected by technological opportunities which vary from a technological class to another and which makes the technological activity of a given firm more profitable in some fields. Technological opportunity and appropriability have often been designated as technology push forces (Rosenberg, 1983). These exogenous factors from the supply side of innovation push the innovative activities bringing pressures on such activities.

A significant part of the recent literature on the theory of industrial organization has been concerned with a better analytical understanding of strategic behaviors adapted by firms engaged in R&D activities. Three incentives that determine the resources allocated to R&D are at the core of the recent interest devoted by economists to these questions (Cohen, Levinthal 1989). First, firms may undertake R&D activities to enhance their profit by pursuing new product and process innovation (***profit incentive***) and second, to enhance their market share (***strategic advantage*** over their rivals). Indeed, if a firm knows that its rivals are engaging in R&D, it will see its own competitive position as being a threat (***competitive threat***). In a same vein, a firm failing to maintain a current position and being replaced by a rival will suffer a loss (***replacement effect***). A monopolist does not fear to be replaced by a rival and therefore, there is not strategic threat. A third incentive, for a firm to engage in R&D consists in developing and maintaining its broader capabilities to assimilate and exploit externally available innovation.

Behavioral models under oligopolistic market environments have been developed in economic theory. Rather than competing by prices changes, oligopolistic firms prefer to turn to product differentiation and quality improvements in order to preserve their market share. In industries characterized by a high R&D intensity, technology is a main component of the non-price competition. As pointed out by Cohen (1995), the empirical literature on technological strategic interactions remains a largely neglected issue. Indeed, there is an astonishing gap between the abundance of theoretical models of R&D rivalry and the lack of real empirical examination of the extent of R&D competition. Yet, the first theoretical arguments developed by Scherer (1967) showed that the increase of R&D efforts of a firm will generally stimulate R&D expenditures of competitors.

In the eighties, game-theoretic models of R&D rivalry rejuvenated the question of the role of strategic interactions. As shown by these models, the competitive threat resulting from higher engagements of rivals in R&D is a key determinant to explain the amount of resources allocated to R&D by a firm. However, the limited empirical evidence on technological strategic interactions does not allow one to conclude whether this point really matters.

1.4 Public policies.

Public authorities may play an important role in pursuing policies that enhance, promote and support innovative and economic performances.

Indeed, for a long time, activities aimed at increasing the stock of knowledge have been neglected by policy-makers. Yet, after sudden adjustment of oil prices in the early 1970's and worsening of the economic situation that followed, it became clear that both physical and human knowledge capitals were in reality at the root of economic growth and welfare. Policy-makers realized that those nations that will excel at creating new knowledge and transforming it into new technologies, products and processes will also have a higher chance in increasing their welfare. This has led to a greater policy attention paid to processes of technological activities.

Four main axes of policies that favor innovation may be distinguished:

- Policies that overcome the failures associated with market of knowledge, i.e. appropriability, uncertainties, indivisibilities;
- Technology policies on the supply side of innovation;
- Technology policies that encourage the adoption of innovations;
- Competition policies.

The imperfect appropriability of innovative outcomes creates a wedge between the private and social return to R&D. In order to reduce this wedge, several public policies can be implemented. The first kind of policies can be related to measures aimed at rising the expected returns by lowering the costs of doing R&D. Among these measures, direct or indirect subsidies as well as measures that facilitate the exploitation of economies of scale can be mentioned. Another way to reduce the gap between private and social returns to R&D consists in directly or indirectly restricting the exploitation of knowledge. Protection through patents or trade marks is referred to as a direct restriction to such exploitation. Measures favoring the internalization of externalities generated by R&D activities as well as vertical strategies developed by innovative firms, are said to be indirect restrictions.

Subsidies implemented to increase the private return to R&D can take several forms. The two most common are tax credits based on total R&D expenditures and levy/grant systems, i.e. lump sum taxes. As pointed out by Spence (1984), subsidies have added benefits: they lower entry barriers, increase competition, lower margins and improve allocative efficiency. However, subsidies are not easy to implement because they require from the policy maker an assessment of the wedge between the private and the social return to R&D. Moreover, these gaps are likely to vary across industries if not from one country or geographic area to the other. In addition, subsidies may actually reward creative accounting practices or encourage firms to undertake second rate R&D projects that have little commercial promise (Stoneman, 1987).

A second type of policy aimed at reducing the costs of doing R&D and consequently at increasing the returns to this activity, consists in adopting measures in order to restructure a firm or an industry with the view of facilitating the exploitation of economies of scale in R&D. Indeed, such scale economies should help firms to reduce their fixed costs and moderate the issue of indivisibilities of their R&D activities.

Among the methods at hand to restrict directly the exploitation of knowledge, the patent system is one of the most commonly used by innovators. Indeed, applying for a patent or a trade mark allows an innovator to assign property rights to himself and as a result to circumvent the issue of non-excludability. In addition, the public disclosure of the patent document favors a maximum diffusion of knowledge.

Measures aimed at internalizing the externalities generated by R&D activities take the form of indirect methods to restrict the use or dissemination of knowledge. Among these measures, we can distinguish between horizontal and vertical strategies. Co-operative research activities such as joint ventures typically refer to the former type of strategy. In addition, technological co-operation involves further advantages such as increasing the benefits from the cost sharing, risk pooling, exploiting economies of scale in R&D, eliminating excessive duplication of R&D projects and pooling of complementary skills. On the other hand, the main drawback of co-operative activities is that it creates monopoly in both the R&D and output markets which in turn generates price distortions. One of the main raisons underlaying the development of vertical strategies is the need to have access to specialized complementary assets in order to commercialize or product the innovation.

In addition to these policies, firms may improve their appropriability by keeping the outcomes of their innovative activities secret. They can also increase the demand for their innovations by increasing their sales or marketing efforts. Finally, being the first to innovate confers certain advantages such as lead time and learning curve advantages.

1.5 Results of technological activity.

Patent statistics are the most widely used indicator for the measurement of the output of technological activities and therefore they constitute a convenient measure of the effectiveness of technological activities. However, many economists have questioned the reliability and validity of patents as a measure of the outcomes of technological activities. One of the main criticism addressed to patent data is that since they are a record of invention, they occur at an early stage of the process of technological change. Consequently, patents are often treated as an intermediate output of technological activities. Another drawback of patent measures is that not all new inventions are patented and patents vary greatly in their economic impact (Pakes and Griliches, 1984). One reason is that inventions have to be successfully developed into marketable product or process innovations in order to receive a positive economic value.

According to Rosenberg (1983), technical progress is constituted by certain types of knowledge that make it possible to produce a greater volume of output or qualitatively superior output from a given amount of resources. Another direct consequence of technological change is that it generally affects the efficiency of the production factors, and as a result, the demand for these inputs. In the neoclassical tradition, three kind of effects of technological change are distinguished: neutral, labor-saving and capital-saving. Hence, a new technology is said to be neutral when it raises the marginal productivity of labor and capital in the same proportion and is said to be labor-saving or capital-saving when it raises the marginal productivity of capital more or less than that of labor, the amounts of the factors being unchanged (Robinson, 1938).

Similarly, technological change has been classified according to whether it increases output (Hicks neutrality, i.e. the marginal rate of substitution is left unchanged as a constant capital-labor ratio), labor (Harrod neutrality, i.e. the capital-output ratio is left unchanged at a constant rate of return to capital), capital (Solow neutrality, i.e. the labor-output ratio is left unchanged at a constant wage rate). It should still be noted however, that in practice it is not obvious to disentangle between these three types of effects.

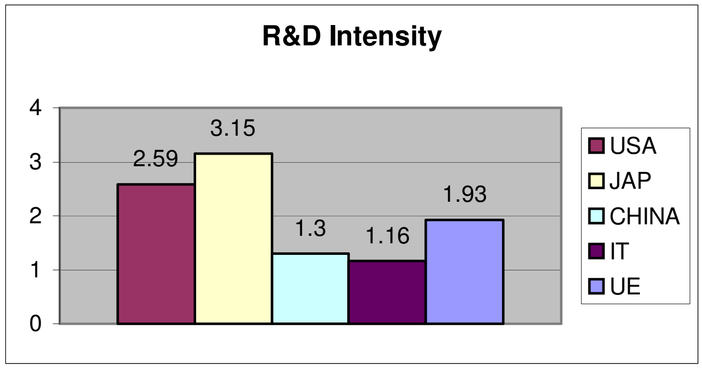
For more than 30 years, economists have been trying to quantify the contribution of technological progress upon economic growth (see, for example, Abramowitz (1956) or Solow (1957)).

Though the numerous studies which have attempted to carry out this measurement exercise are full of pitfalls, both conceptual and methodological, they all point to the recognition of the major role played by technical progress in economic growth, leaving the increase in quantity of capital and labor input accounting for a very small share.

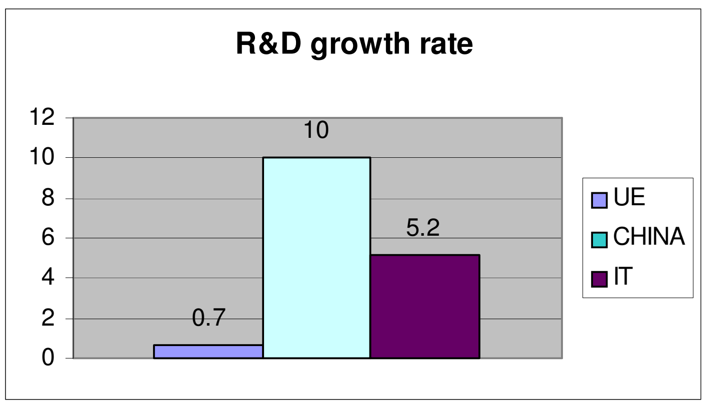
One economic incentive that motivates firms to undertake technological activities is the expectation of some economic benefits, net of the incurred costs, derived from the innovation. These profits may arise for several reasons: decreased production costs, in the case of cost reducing innovations, increased market share thanks to new product innovations replacing old technologies become obsolete: royalties or fixed fees, e.g. an independent innovator licensing his discovery to a firm. It should be noted that the profit incentive to undertake innovative R&D activities may not be the same under the different market structures and according to whether the innovator is an incumbent or an entrant. For instance, as shown by Scherer (1980), when a cost-reducing process innovation is introduced to a perfectly competitive market, the innovator can appropriate the full cost reduction over an increased volume output, since his actions will not influence market price. At the other end, in a monopoly the profit incentive is lower since the innovator faces a declining demand curve, and as a result, he has to share his rent with the consumers. In addition, the lower cost curve resulting from the cost-reducing innovation will diminish prices and increase output. However, for entrants, this conclusion is somewhat different. As Arrow (1962) demonstrated, not only entrants benefit from lower costs resulting from their process innovation, but also from raised profitability inherent to monopoly.

Statistics about R&D activity in different countries.

Graph 1. R&D intensity[2]

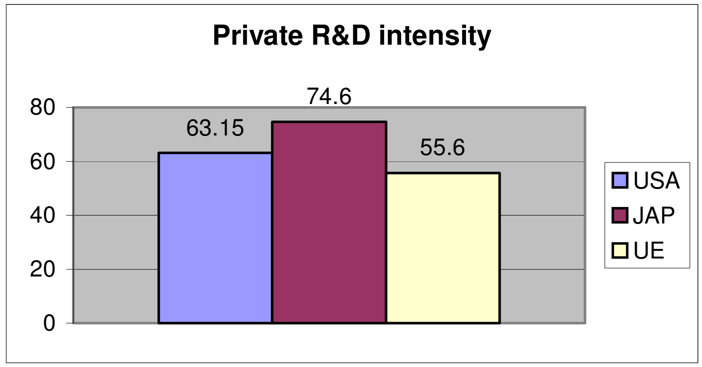


Graph 2. R&D growth rate

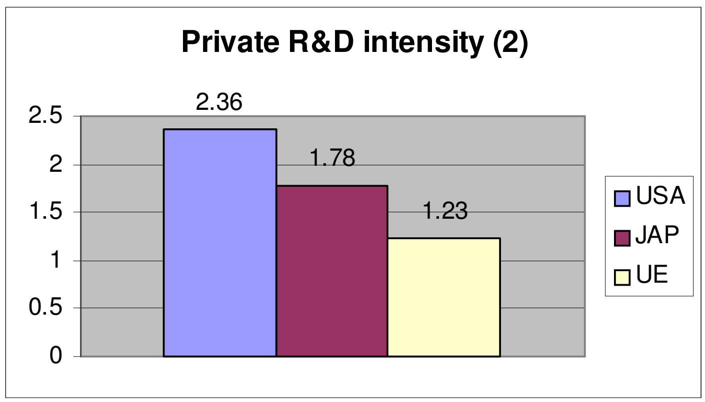


[2] The data are obtained from own calculations on OECD source results. R&D is equal to the ratio between R&D capital stock and the net sales.

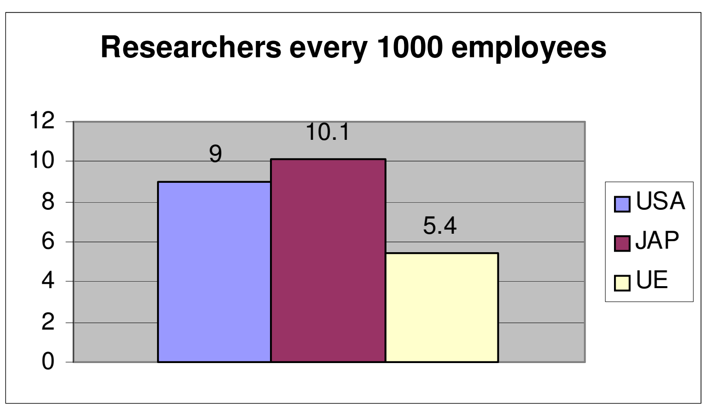
Graph 3. Private contribution to R&D intensity[3]



Graph 4. Private R&D intensity[4]



Graph 5. Average number of researchers



[3] Here we show the contribution in percentual of R&D intensity due to private sector.
[4] Here we show the R&D intensity of private sector.

2. R&D Spillover and Absorptive capacity: A Survey.

2.1 Production function approach.

Various approaches have been adopted in the attempt to estimate the effect of spillovers. The most widely used has been to introduce a measure of potential pool of external knowledge into a standard production function framework (Griliches, 1979), either at the firm or at the more aggregate (industry, region, country) level, with the ultimate aim to asses the impact of accessible external R&D on total factor productivity (TFP).

Formally we get:

$$\ln Yit = \alpha_i + \lambda_t + \beta_1 \ln C_{it} + \beta_2 \ln k_{it} + \beta_3 \ln L_{it} + \gamma \ln X_{it} + \varepsilon_{it} \qquad (1)$$

where: ln is the natural logarithm,

L_{it} is the employment of firm i at time t ,

K_{it} is the stock of R&D capital,

Y_{it} is the value-added of firm i at time t,

C_{it} is the stock of physical capital,

α_i is the firm's specific effect,

λ_t is a set of time dummies,

X_{it} is a vector of spillover components,

γ is its associated vector of parameters,

ε_{it} is the disturbance term.

Estimation error imposed by the use of sales, instead of value-added if not available, as a proxy for output will be confined to the constant term if the charges are some fixed proportion of sales. This assumption will be valid in a panel data setting where a firm fixed-effects model is used. To the extent that variation in materials and energy fraction of sales is an industry or region fixed effect, this assumption should be reasonable in the cross-section through use of industry- and state-specific dummies.

In order to construct the stock of R&D capital it is possible to use the permanent inventory method (Griliches, 1979). This method assumes that the current state of knowledge is a result of present and the past R&D expenditures:

$$
\begin{aligned}
Kit &= (1-\partial)K_{it-1} + R_{it} = \\
&= R_{it} + (1-\partial)R_{it-1} + (1-\partial)^2 R_{it-2} \ldots = \\
&= \sum_{\tau=0}^{\infty} (1-\partial)^{\tau} R_{it-\tau}
\end{aligned}
\tag{2}
$$

where Kit is the knowledge capital or the own R&D stock of firm i at time t

Rit is the R&D expenditures and

$1-\partial$ is the rate of depreciation of the knowledge capital.

Regarding the value of the depreciation rate, most studies assume a depreciation rate of 15%. By assuming a log-log functional form of Cobb-Douglas production function, Griliches, Mairesse, (1983,1984) and Hall, Mairesse (1995) have experimented with different values of ∂ and they have found small changes if not at all in the estimated effects of R&D capital.

The initial knowledge capital is constructed as in equation (2), and by assuming a growth rate of R&D equal to *g:*

$$k_{i0} = R_{i0} \sum_{\tau=0}^{\infty} \frac{(1-\partial)^{\tau}}{(1-g)} = \frac{R_{i0}}{(g+\partial)} \qquad (3)$$

Here also, a growth rate of 5% is usually assumed. Regarding the timing of R&D effects, it is to be expected that R&D activities do not have an immediate impact on firms' economic performances. Evenson (1968) examines aggregate data for U.S. agriculture and concludes that the lag structure of R&D takes an inverted V shape. He concludes that the peak weight from R&D flows is at five to eight year lags and little contribution is received from R&D expenditure at lags in excess of 10 to 16 years. But Wagner (1968) provides survey evidence that these lags are much shorter for industrial R&D, perhaps reflecting the more applied nature of private R&D expenditures.

Griliches (1973) and Terleckij (1974) suggested also an alternative method to construct the R&D stock of knowledge. This approach estimates the rate of returns to R&D instead of its elasticities. To this end, the firm's own R&D capital is replaced by the firm's R&D intensity measured as the ratio between the level of R&D expenditures and the firm's output, i.e. net sales or added value.

2.3 Knowledge production function approach.

Difficulties in measuring prices precisely and adjusting them for quality improvements make the production function approach not particularly suited to distinguish technological externalities from pecuniary externalities.

For this reason, some authors have implemented the "knowledge production function", methodological framework introduced by Pakes and Griliches (1984). 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 intermediates inputs and is not evaluated using prices, but simply the quantity of innovations, it minimises the role of rent externalities.

Patents are count data and occur in integers. These characteristics are known to generate bias in estimates of the log-linear models and motivate the estimation of alternative non-linear models[5].

Regardless of the model chosen (linear versus non-linear), a concern in the estimation of equations resides in the complex structure of the individual effect, which is characterized by correlation across panels, hence by a residual variance-

[5] See Cincera (1997) for a deep analysis for most econometric techniques used for count data models.

covariance matrix that is not longer block diagonal. If such correlation is ignored, inferences based on OLS or random effect estimation might then be misleading since estimated standard errors are biased downward. By contrast, fixed effect estimates are conditional on the individual effects, which leaves the standard errors unaffected. Furthermore, fixed effects methods ensure consistency in the presence of correlation between the explanatory variables and the individual effects. For the above reason, fixed effect methods, although inefficient, are to be preferred.

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 (Hall, Hausman, Griliches, 1984).

This model estimates the relationship between the arrival rate of patents and the independent variables. The dependent variable *yit* is assumed to have a Poisson distribution with parameter μ_{it} which, in turn, depends on a set of exogenous variables *xit* according to a log-linear function:

$$\ln \mu_{it} = \alpha_i + \beta x_{it} \qquad (4)$$

where α_i captures the individual effect.

One way to estimate this model is to run the conditional Poisson regression by maximum likelihood, including the dummy variables for all individuals (less one) to directly estimate the fixed effects. If there is not a specific interest in the fixed effects or if their number is large conditional maximum likelihood represents an alternative method. Conditioning on the count total for each individual, $\sum_i y_{it}$, it leads to a conditional likelihood proportional to:

$$\prod_i \prod_t \left(\frac{\exp(\beta x_{it})}{\sum_s \exp(\beta x_{is})} \right)^{y_{it}} \qquad (5)$$

which no longer includes the α_i parameters.

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, i.e. $E(y_{it}) = V(y_{it}) = \mu_{it}$. This is an undesired feature whenever there is an additional heterogeneity not accounted for by the model, when the data show evidence of overdispersion. Such problem might be dealt with by assuming that the variable *yit* has a negative binomial distribution (Hall, Hausman, 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 Hall, Hausman, Griliches (1984) negative binomial model it is assumed that:

$y_{it} / \gamma_{it} \sim$ Poisson (γ_{it}) and $\gamma_{it} / \theta_i \sim$ Gamma ($\lambda_{it}, 1/\theta_i$), where θ_i is the dispersion parameter and $\ln \lambda_{it} = \beta x_{it}$. This leads to the following density function:

$$f(y_{it}/\lambda_{it},\theta_i)=\frac{\Gamma(\lambda_{it}+y_{it})}{\Gamma(\lambda_{it})\Gamma(y_{it}+1)}\left(\frac{1}{1+\theta_i}\right)^{\lambda_{it}}\left(\frac{\theta_i}{1+\theta_i}\right)^{y_{it}} \quad (6)$$

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

$$\begin{aligned} E(y_{it}) &= \theta_i\lambda_{it} \\ V(y_{it}) &= (1+\theta_i)\theta_i\lambda_{it} \end{aligned} \quad (7)$$

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

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

$$\frac{\Gamma(\sum_t y_{it}+1)\Gamma(\sum_t \lambda_{it})}{\Gamma(\sum_t y_{it}+\sum_t \lambda_{it})}\prod_t \frac{\Gamma(\lambda_{it}+y_{it})}{\Gamma(\lambda_{it})\Gamma(y_{it}+1)} \quad (8)$$

which is free of the θ_i parameters. The likelihood of the entire sample is then obtained multiplying all the individual terms like in (6) and can be maximised with respect to β the parameters using conventional numerical methods.

3.4 The measure of the Absorptive Capacity.

"...a country's potential for rapid growth is strong not when it is backward without qualification, but rather when it is technologically backward but socially advanced".

Moses Abramovitz (1986).

The effects of outside knowledge externalities (spillovers) on own productivity levels depend on own basic research level, which makes us to identify, assimilate and exploit existing information (Cohen, Levinthal, 1989).

To measure the Absorptive Capacity of a firm, there exist different ways in the econometric models.

In the production function approach context, the authors assume that the elasticity of output (or value added) to national or foreign stock of spillovers depend on the chosen measure of Absorptive Capacity, which generally is represented by own R&D capital. The positive effect of the interaction between own R&D capital and the spillover pool term indicates the firm ability to absorb new ideas from outside, while its negative effect gives evidence of necessity to invest more in own R&D. Indeed, in this last case, a firm with low innovation rate cannot use other firms' new ideas and the competitive effect leads to a negative effect of the spillover pool.

In the knowledge production function approach context, the researchers use information about self citations to takes into account the magnitudes of the absorptive capacity. A self citation indicates that a 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 sector the more firms innovating within such sector 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 the absorptive capacity. 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 related technological areas.

2.5 GMM Estimators.

In panel data models, First-Differenced Generalised Method of Moments (GMM)[6] currently appears to be perceived as the best available. In particular, it is useful for autoregressive linear regression models estimated from short panels in the presence of unobserved individual-specific time-invariant (fixed) effect.

Consider an AR (1) model with unobserved individual-specific effects

$$y_{it} = \alpha y_{it-1} + \eta_i + \upsilon_{it} \qquad |\alpha| < 1 \quad (9)$$

for i = 1 to N and t = 2 to T where $\eta_i + \upsilon_{it} = u_{it}$ has the standard error components structure

[6] See Hansen (1982) for the general description of the GMM models.

$$E(\eta_i) = 0, E(\upsilon_{it}) = 0, E(\eta_i \upsilon_{it}) = 0 \text{ for i = 1 to N and t = 2 to T.} \quad (10)$$

We assume that the transient errors are serially uncorrelated

$$E(\upsilon_{it}\upsilon_{is}) = 0 \quad \text{for i = 1 to N and } s \neq i \quad (11)$$

and that the initial conditions yi1 are predetermined

$$E(y_{i1}\upsilon_{it}) = 0 \text{ for i = 1 to N and t = 2 to T.} \quad (12)$$

These assumptions imply the m=0.5* (T-1)* (T-2) moment restrictions which can be compactly written:

$$E(Z_i^{'}\Delta\upsilon_i) = 0 \quad (13)$$

where *Zi* are (T-2)*m matrix given by

$$Z_i = \begin{bmatrix} y_{i1} & 0 & 0 & \ldots & 0 & \ldots & 0 \\ & y_{i1} & y_{i2} & \ldots & 0 & \ldots & 0 \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\ 0 & 0 & 0 & \ldots & y_{i1} & \ldots & y_{iT-2} \end{bmatrix} \quad (14)$$

and $\Delta \upsilon_i$ is the (T-2) vector $(\Delta \upsilon_{i3}, \Delta \upsilon_{i4}, ..., \Delta \upsilon_{iT})'$. These are the moment restrictions exploited by the standard linear first-differenced GMM estimator, implying the use of lagged levels dated t-2 and earlier as instruments for the equations in first-differences (Arellano, Bond, 1991). This yields a consistent estimate of α as $N \to \infty$ and T is fixed.

However, this first-differenced GMM estimator has been found to have poor finite sample properties, in terms of bias and imprecision, in one important case.

This occurs when the lagged levels of the series are only weakly correlated with subsequent first-differences, so that the instruments available for the first-differenced equations are weak (Blundell and Bond, 1998). In the AR (1) model of equation (9), this occurs either as the autoregressive parameter (α) approaches unity, or as the variance of the individual effects (η_i) increases relative to the variance of the transient shocks (υ_{it}).

Simulation results reported in Blundell and Bond (1998) show that the first-differenced GMM estimator may be subject to a large downward finite-sample bias in these cases, particularly when the number of time periods available is small. This suggests that some caution may be warranted before relying on this method to estimate autoregressive models. It may be that the presence of explanatory variables other than the lagged dependent variable, and more particularly the inclusion of current and lagged values of these regressors in the instrument set, will improve the behaviour of the first-differenced GMM estimator.

How can we detect whether serious finite sample biases are present? One simple indication can be obtained by comparing the first-differenced GMM results to alternative estimates of the autoregressive parameter (α). In the AR (1) model of equation (9), it is well known that OLS levels will give an estimate of α that is biased upwards in the presence of individual-specific effects (Hsiao, 1986), and that the Within Group estimator will give an estimate of α that is seriously biased downward in short panels (Nickell, 1981). Thus a consistent estimate of α can be expected to lie in between the OLS levels and Within Groups estimates. If we observe that the first-differenced GMM estimate is close or below the Within Group estimate, it seems likely that the GMM estimate is also biased downward, perhaps due to weak instruments. In these cases, it may be appropriate to investigate the quality of the instruments, by studying the reduced form equations for Δy_{it-1} directly, or to consider alternative estimators that are likely to have better finite sample properties in the context of persistent series.

To obtain a linear GMM estimator better suited to estimating autoregressive models with persistent panel data, Blundell and Bond (1998) consider the additional assumption that

$$E(\eta_i \Delta y_{i2}) = 0 \quad \text{for i =1 to N (15)}$$

This condition holds if the means of the *yit* series are constant through time for periods 1,2,…T for each individual. This assumption yields T – 2 further linear moment conditions

$$E(u_{it}\Delta y_{it-1}) = 0 \text{ for I = 1 to N and t = 3,4…T} \quad (16)$$

These allow the use of lagged first-differences of the series as instruments for equations in levels, as suggested by Arellano and Bover (1995).

We can then construct a GMM estimator which exploits both sets of moment restrictions (13) and (15). This uses a stacked system of (T – 2) equations in first-differences and (T – 2) equations in levels, corresponding to periods 3 to T for which instruments are observed. The instrument matrix can be written as

$$Z_i^+ = \begin{bmatrix} Z_i & 0 & 0 & \dots & 0 \\ 0 & \Delta y_{i2} & & & 0 \\ 0 & 0 & \Delta y_{i3} & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & 0 & \dots & \Delta y_{iT-1} \end{bmatrix} \quad (17)$$

where *Zi* is given by (14). The complete set of second-order moment conditions available can be expressed as

$$E(Z_i^{+\prime} u_i^+) = 0 \quad (18)$$

where $u_i^+ = (\Delta \upsilon_{i3,} ... \Delta \upsilon_{iT}, u_{i3}, ... u_{iT})'$.

The system GMM estimator thus combines the standard set of equations in first-differences with suitably lagged levels as instruments, with an additional set of equations in levels with suitably lagged first-differences as instruments. The validity of these additional instruments can be tested using standard Sargan tests of overidentifying restrictions, or using Difference Sargan or Hausman comparisons between the first-differenced and system GMM results (Arellano and Bond, 1991).

We can also consider a static model instead of dynamic one.

In the following model:

$$y_{it} = \beta x_{it} + \eta_i + \upsilon_{it} \qquad (19)$$

where *xit* is correlated with η_i and exogenous in the sense that

$$E(x_{it}\upsilon_{is}) = 0 \text{ for i =1 to N and s} \le t \quad (20)$$

Taking first differences to eliminate the individual effects η_i the moment conditions

$$E(x_{it-s}\Delta \upsilon_{it}) = 0 \text{ for t = 3 to T and s} \geq 2 \quad (21)$$

are available. Lagged values of endogenous *xit* variables dated t-2 and earlier can then be used as instruments for the equations in first-differences.

If *xit* are uncorrelated with the individual-specific effects

$$E(\eta_i \Delta x_{it}) = 0 \text{ for i = 1 to N and t = 2 to T} \quad (22)$$

and the following moment conditions are available:

$$E(\Delta x_{it-1} u_{it}) = 0 \quad \text{for i =1 to N and t = 3 to T} \quad (23)$$

then suitably lagged first-differences of endogenous *xit* variables can be used as instruments for the level equations (so the system GMM is implemented).

The system GMM can be run with both production function approach and knowledge production function approach.

2.6 EMPIRICAL EVIDENCE.

In table 1, we show econometric results for models based on the production function approach.

Coe and Helpman (1995) point out the effects of innovation efforts on technological progress. Their dataset regards 21 OECD (+ Israel) countries over 1971-1990. Econometric estimates show that the R&D capital leads to higher elasticity of productivity (value added) with respect to the domestic stock of spillovers for the seven major countries (G7), and to higher elasticity of productivity (value added) with respect to the foreign stock of spillovers for open smaller economies[7]. In their work, they implement Levin, Lin (1992,1993) cointegration tests.

Wu, Popp, Bretschneider (2001) improve upon Coe, Helpman's model of international R&D spillover (1995)[8], using seemingly unrelated regression (SUR), to include interdependence among national economies and allow for variations in coefficients across countries. They show that the impact of foreign knowledge spillover on national productivity is not universal, just as domestic innovative activities, but context dependent: positive in some cases, negative in others. Indeed, knowledge spillover can increase the productivity of domestic research by enlarging the knowledge pool available for further R&D, and can be used in the production process. Meanwhile, the knowledge spillovers also signify the foreign

[7] Keller (1998) compares elasticity of domestic productivity with respect to foreign R&D estimated by Coe and Helpman (1995) with an elasticity which is based on counterfactual international trade patterns. He use Monte-Carlo-based robustness tests.

[8] Also Lichtenberg, Van Pottelsberghe de la Potterie (1998) improve Coe and Helpman's estimates in order to attenuate the aggregation bias.

competition that has to be confronted. Thus, the empirical results suggest that both beneficial and competitive effects from foreign knowledge spillovers are important.

Blomstrom, Sjoholm (1999) utilise unpublished Indonesian microdata to estimate the foreign capital effects on domestic firms productivity. There are not spillovers if the technological gap is too large or if Government introduce restrictions on foreign control. The authors find that the positive spillover effect is higher for non-exporter firms because spillovers affect efficiency (in terms of costs) and competitiveness of the firms.

Aitken, Harrison (1999) carry out econometric estimates on 4000 Venezuelan firms over 1976-1989. They find a positive relationship between increased foreign equity participation and plant performance suggesting that individual plants do benefit from foreign investment (only for firms with less than 50 employees) – "own-plant-effect" – and productivity in domestically owned plants declines when foreign investment increases (negative spillover effect on market-stealing effect).

If we add up the positive own-plant effect and the negative spillover on balance the impact of foreign investment on domestic plant productivity is quite small.

Kinoshita (2000), using firm-level data on Czech manufacturing firms between 1995-1998, show that the learning effect is far more important than the innovative effect in explaining the productivity growth of a firm and there is no evidence of technology spillovers to local firms from having a foreign joint venture partner.

Another interesting finding is that the rate of technology spillovers from FDI varies greatly across sectors. In oligopolistic sectors such as electrical machinery and radio&TV, there exists a significant rate of spillovers from having a large foreign presence. Also, R&D investment has a higher rate of return in these sectors. On the other hand, less oligopolistic sectors such as food and non-metallic mineral water show no evidence of spillovers despite the large presence of foreign investors in these sectors.

Girma, Gorg (2002) focus on the role of absorptive capacity in determining whether or not domestic firms benefit from productivity spillovers from FDI. They analyse this issue using firm level data for the electronics and engineering sectors in the UK over 1980-1992. They distinguish the effect of FDI in the same sector and region from FDI in the same sector but outside the region. They think that standard OLS or GMM techniques which concentrate on the conditional mean function of the dependent variable are unlikely to be adequate analytical tools, because in the presence of heterogeneous productivity processes, it is more appropriate (and arguably more interesting) to examine the dynamics of productivity at different points of the distribution rather than "average" properties (i.e. conditional means). To do this, they use the quantile regression technique introduced by Koenker and Bassett (1978). Absorptive capacity is measured as the gap in Total Factor Productivity (TFP) between domestic firm and industry leader. The findings suggest that both absorptive capacity and distance matter for productivity spillover benefits. There is a u-shaped relationship between absorptive capacity and productivity spillovers from FDI in the region, while there is an inverted u-shaped relationship for spillovers from FDI outside the region.

This pattern seems consistent with the idea that positive productivity spillovers from FDI are localised and only firms located within the same region are set to benefit. If FDI is located far away from the establishment the negative competition effect of FDI appears to dominate.

Grunfeld (2004), through analysis on data of 105 firms of small open economy of Norway over 1989-1996, studies how the productivity effects of own R&D interact with 3 sources of R&D spillovers: domestic intermediates, imports, FDI. He finds that domestic R&D spillovers through the use of domestic intermediates have a significantly stronger impact on productivity. Spatial proximity between firms and industries appears to improve the flow of knowledge and technology, increasing the productivity effect through R&D spillovers.

Table 1. Production function Approach:
Comparative analysis on Foreign Spillovers.

STUDY	DATA	MODEL	ESTIMATION	S.E.
Coe, Helpman (1995)	21 OECD countries over 1971-1990	Fixed-effect model	0.078 (domestic) 0.294 (foreign)	0.04
Wu, Popp, Bretschneider (2001)	19 OECD countries	SUR model	0.084 (min dom.) 1.022 (max dom.) -0.847 (min for.) 0.750 (max for.)	6.59 14.99 -0.08 21.18
Blomstrom, Sjoholm (1999)	29 Industries in India, 1991	Fixed-effect model.	1.00	15.62***
Aitken, Harrison (1999)	4000 venezuelan firms, 1976-1989	OLS, FD	0.105 (plant), OLS -0.267 (sector), 0.003 (plant),FD -0.238 (sector),FD	0.03 0.06 0.04 0.07
Kinoshita (2000)	Czech firms 1995-1998	OLS	-0.007 0.026	0.01 0.06
Girma. Gorg (2002)	49-four digit industries in UK 1980-1992	Quantile regression model	Electronics 0.317 -0.093 Engineering -0.751 0.349	0.20** 0.09 0.15** 0.15*
Grunfeld (2004)	105 firms in Norway 1989-1996	Fixed-effect model	0.007 0.235 0.054 -0.020	0.01 0.04** 0.02** 0.01*

Note: *Significant at the 10% level; **Significant at the 5% level;
***Significant at the 1% level.

In table 2, we summarize empirical findings of models considering different dimensions of knowledge spillovers: technological and geographic.

Jaffe (1986) introduces an interesting procedure to estimate spillover effects. Indeed, he constructs a technological space for the firms, and computes the proximity measure among them by the uncentered correlation coefficient, described in the previous section. In particular, he considers the number of patents as dependent variable and implements different econometric models, OLS, First-Differences and 3 Stages-Least-Squares (3SLS). He finds a positive effect of spillover pool on the firm productivity.

Bernstein, Nadiri (1989) estimate a model of production and investment, based on the theory of dynamic duality. There are three effects associated with intra-industry R&D spillovers (computed by the unweighed sum of R&D spending of other firms in the same industrial sector with respect to the firm considered in the analysis): a cost-reducing effect, that is, costs decline as knowledge expands for externalities-receiving firms; a factor-biasing effect, in the sense that production structures are affected, as factor demands change in response to the spillovers; finally, capital adjustment effects, because the rates of capital accumulation are affected by R&D spillovers. The existence of R&D spillovers implies that the social and the private rates of return to capital differ. The social rate of return to R&D is defined as the cost minimization problem for all firms in the industry, while the private rate of return to R&D is defined as the cost minimization matter for individual firm. The authors estimate that the social return exceeds the private return in each industry. However, there is significant variation across industries in the differential between the returns.

Bottazzi, Peri (2002) estimate the effect of research externalities across geographic space, in generating innovation. They do so, using R&D and patent data on 86 European regions over 1977-1995. They claim that new knowledge, when codified, is available to everybody and therefore is a public good which influences the potential for new ideas everywhere in the world. However, new ideas which are not perfectly codified are embodied in people. Thus, they estimate the elasticity of innovation to R&D and they find it to be positive and significantly different from 0 only for R&D done within 300 km of distance from a region. Its magnitude, though, is quite small: doubling R&D in a region would increase by 2-3% the patenting activity in another region within 300 km of distance. The small size and the short range of these effects is consistent with the idea that such spillovers are the result of diffusion of non-codified knowledge between people who have frequent interactions. There is reason to claim that in Europe people commute and interact quite frequently within regions, while much less so if a longer trip is required. Moreover they commute and interact more within than across countries and therefore a small border effect on these spillovers is detected. The range of these spillovers could very well be that of frequent face-to-face interactions, while the rest of knowledge flows is codified format and is not sensitive to the distance.

Orlando (2000) examines whether the geographic and technological distance attenuate inter-firm spillovers from innovative activity. Parameter estimates obtained in a production function framework indicate that spillovers are significant and important from geographically and technologically proximate R&D stocks. Results from the general analysis suggest that the importance of geographic proximity is conditional on technical relation between spillover sending and receiving units. Spillover from R&D outside a firm's own narrowly defined industry group are increasing in geographic proximity. However, R&D spillovers from within a firm's own industry are insensitive to distance. Conversely, evidence that technological similarity accentuates spillover is insensitive to distance between spillover sending and receiving units. In contrast, returns from the R&D of technologically distant firms are sensitive to geographic proximity to the spillover receiver. The finding that R&D spillovers are largest among firms in the same narrowly defined industry may support arguments in defence of increased concentration in particular industries. To the extent that dominant firms internalise a larger fraction of total returns to innovative activity they will invest in more of it. Among technologically similar firms, the partial spillover enhancing effect of geographic proximity is much less significant. A defence of mergers between firms in a particular geographic region therefore may not be justified by the internalisation of knowledge spillover argument.

Globerman, Shapiro, Vining (2003) study, through the analysis of 3000 Canadian industries and regions over 1999-2002, the role that the agglomeration of firms in specific locations (clusters), and the technological spillovers within and between clusters, plays in conditioning the performance and innovative behaviour of the firms. They find that a very limited number of economic locations in Canada contribute to the growth of the firms. Indeed, the city of Toronto arguably comprises the clearest example of a successful geographic location for Canadian companies. The results provide some clear evidence of spillovers from centres of clustering. In particular, it shows that firms located closer to Toronto grow faster than firms located further away, all other things constant. Spillover benefits from

USA clusters are more difficult to identify statistically than those from the Toronto cluster, perhaps suggesting the presence of border effects.

Table 2. Comparative analysis based on technological or geographic proximity.

STUDY	DATA	MODEL	ESTIMATION	S.E.
Jaffe (1986)	432 firms from NBER R&D panel (data centered on 1973 and 1979)	OLS First-Diff 3SLS	Spillover effect 0.628 (OLS) 0.179 (First-Diff) 0.509 (3SLS)	0.11 0.06 0.10
Bernstein, Nadiri (1989)	4 US industries in 1965-1978	Non-linear Full Information Maximum Likelihood (FIML)	Chemicals -0.0004 -0.0003 Petroleum -0.1908 -0.0567 Machinery -0.0004 -0.000033 Instruments -0.0014 -0.0053	 0.00 0.00 0.07 0.02 0.00 0.00 0.00 0.00
Bottazzi, Peri (2002)	86 European regions over 1977-1995	OLS	Spillover 0-300km 0.025 300-600km -0.007 600-900km -0.004 900-1300km -0.007 1300-2000km -0.018	0.01** 0.01 0.01 0.01 0.01
Orlando (2000)	515 US firms 1972-1995	Within, Between Groups	Within 0.010 0.005 0.011 -0.000 Between 0.032 0.009 0.030 0.002	 0.00** 0.00** 0.00** 0.00 0.01** 0.00** 0.00** 0.00**
Globerman, Shapiro, Vining (2003)	300 high technology companies in Canada 1999-2002	OLS	-0.061	0.02***

Note: *Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level.

In table 3, the empirical evidence for the main models based on the knowledge production approach is reported.

Crépon, Duguet (1998) examine two aspects of the R&D relationship. First, they look at the constant returns to scale result obtained when variables are used in levels. Second, they examine the dynamics of R&D-patent relationship, evaluating whether past patenting reveals shifts in this relation. To do so, they implement a GMM model with multiplicative fixed effects. The estimated return to R&D approximately 0.3. The past number of patents has a non-linear effect: small but positive numbers of past innovations affect positively the production of innovation but the effect slowly vanishes as the number of innovations increases.

Almeida, Kogut (1999) consider social and economic linkages among different activities to generate and sustain the growth. They implement a logistic regression analysis, taking into account patent citations of 18 regional clusters[9]. They find that the localization of patentable knowledge varies across regions (tacit or no-codified knowledge) and that ideas are transferred through labor markets. Indeed, this analysis show that intraregional mobility has a positive effect on the probability to generate a new idea, while the interregional mobility has a negative effect.

Maurseth, Verspagen (2002), using a patent citations analysis on Europe, implement a Tobit regression and a negative binomial regression to examine whether geographical distance, national borders and language differences impede

[9] Porter, Stern (2000) use the international patenting rates to model the production of ideas.

knowledge flows in this continent. They also investigate the extent to which knowledge flows are confined to regions with particular technological specialisation. The results show that geographical distance has a negative effect on knowledge flows. These are larger within countries than between regions located in separate countries, as well as within regions sharing the same language. Furthermore, knowledge flows are industry specific and regions' technological specialization is an important determinant for their technological interaction. Localised spillovers, confined within country borders or by geographic distance, are potentially a source of economic divergence. If regions are only able to receive spillovers from nearby regions, they have to rely on smaller knowledge bases for R&D and production. The finding that technology flows are both industry-specific and confined by geography, language and country borders, indicates that regional polarisation in Europe may indeed be a reality.

Cincera (1997) attempts to measure the impact of the technological factors on the patenting activity at the firm level. He estimates different econometric models: Poisson, Negative Binomial Distribution (NBD), the General Event Count model (GEC) for a more flexible conditional mean-variance relationship than the Poisson and the NBD, a conditional Poisson model and two non-linear GMM estimators. He finds a high sensitivity of the results among the different models. However, results suggest a significant effect of R&D stock on the patenting activity.

Mancusi (2004) provides an empirical assessment of the national and international knowledge spillovers on innovation at a finely defined sectoral level for six major industrialised countries over the period 1981-1995. The measure of knowledge spillovers are built using citations included in the patent applications at the European Patent Office (EPO). In particular, she implements a Constrained Negative Binomial model (CNB) and an Unconstrained Negative Binomial one (UNB). The results presented give evidence of the importance of such spillovers in increasing innovative productivity.

Table 3. Knowledge production function approach: Comparative analysis.

STUDY	DATA	MODEL	ESTIMATION	S.E.
Crépon, Duguet (1998)	Patent Data from European Patent database 1984-1989	GMM	0.75	0.04
Almeida, Kogut (1999)	Patent citations about US semiconductor industry 1980-1985	Logistic regression	Intraregional Mobility -0.1979 Interregional Mobility -0.0044	0.04*** 0.04
Maurseth, Verspagen (2002)	12432 observations on 112 european regions about patent citations	Tobit NBD (Negative binomial distribution)	-0.38 (Tobit) -0.30 (NBD)	0.02*** 0.02***
Cincera (1998)	181 international large firms over 1983-91 from Worldscope database	Poisson NBD GEC CP NLGMM1 NLGMM2	0.24 0.42 0.44 0.29 0.35 0.31	1.90 2.00 3.50 1.60 6.90 5.80
Mancusi (2004)	Patent citations data on 6 industrialised countries over 1981-1995	CNB UNB	CNB 0.05 0.29 UNB 0.32 0.26	0.01 0.03 0.01 0.01

Note: *Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level

Finally, in table 4 we consider the models trying to quantify the magnitude of the Absorptive capacity of the firms.

Griffith, Redding, Van Reenen (2003) start from a structural model of endogenous growth following Aghion, Howitt (1992)[10], then they provide microeconomic foundations for the reduced-form equations for total factor productivity growth frequently estimated empirically using industry-level data. They think that R&D efforts affect both innovation and the assimilation of others' discoveries (absorptive capacity). Indeed, the theoretical model identifies three key sources of productivity growth: R&D-induced innovation, technology transfer, R&D-based absorptive capacity. While microeconometric literature on R&D and productivity concentrates on the first, the empirical literature on productivity convergence focuses on the second. The authors find that all three sets of considerations are statistically and economically important, and confirm a key empirical prediction of the theory that an interaction term between R&D and distance from the technological frontier should have a positive effect on productivity growth.

Kinoshita (2000) analyses the learning effect of R&D spending by relating it to the size of technology spillovers. That is, R&D affects both two channels: one is through a direct channel, the other is through the absorptive capacity. Results show that innovative R&D is outweighed by absorptive R&D via spillovers from foreign presence in the industry. On the other hand, R&D plays no important role for productivity growth of foreign firms.

[10] Barlevy (2004) developed an endogenous growth model to analyse the interaction between the economic boom and recessions, and R&D capital.

In Grunfeld (2004) the absorptive capacity of an industry, measured in terms of its R&D intensity, helps to take advantage of the R&D content flowing to the industry through imports. Thus, the studies give support to the importance of learning ability in the search of international R&D spillovers. This is not the case however for domestic R&D spillovers. He argues that the negative effect of geographical distance for spillovers can be counteracted by R&D investments that improve the absorptive capacity. This issue is not equally relevant for domestic spillovers since the geographical distance plays a less important role in this case.

Mancusi (2004) implements an econometric model based on knowledge production function approach and to pick up the absorptive capacity of the firms she considers the interaction between the self citations and the spillover pools terms, that is the national and the international stock of spillovers, computed taking into account the patent citations data. The estimation results provide evidence of a positive effect of past research effort on the ability to understand and exploit external knowledge. Indeed, the estimated overall elasticity of patents to absorptive capacity from the fixed effects linear model is equal to 0.16.

Table 4. Comparative analysis on Absorptive Capacity

STUDY	DATA	MODEL	ESTIMATION	S.E.
Griffith, Redding, Van Reenen (2003)	1801 US firms over 1974-90	Within Groups	1.00	0.34
Kinoshita (2000)	Czech firms 1995-1998	OLS	-0.09 0.24	0.04** 0.08***
Grunfeld (2004)	105 firms in Norway 1989-1996	Fixed-effect model	-0.08 -0.05	0.23*** 0.26*** 0.17 0.14
Mancusi (2004)	Patent citations data on 6 industrialised countries over 1981-1995	CNB UNB	CNB 0.03 0.05 UNB 0.02 0.07	0.01 0.01 0.01 0.01

Note: *Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level.

3. Technological proximity based approach.

3.1 Data set and variables

The R&D database has been constructed with the view of setting up a representative sample of the largest firms at the international level that reported R&D expenditures.

The dataset consists of a balanced panel of 964 firms over 1988-1997 (see table 5). For each firm, information is available for net sales (S), number of employees (L), net property, net plant, property&equipment (C), annual R&D expenditures (R) and major industry group according to the Standard Industrial Classification (SIC – 4 digits).

The information on company profiles and financial statements comes from the Worldscope/Disclosure database (2000).

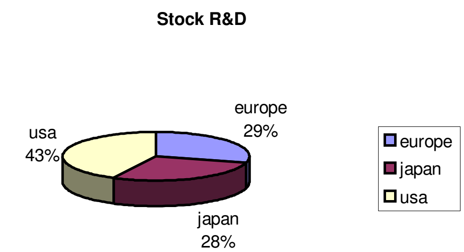
Table 5. Firms across country.

Country	Number of firms	%
Europe	131	0.14
Japan	288	0.30
Usa	545	0.56

All variables have been converted into constant 1995 dollars. Because of non-availability of output deflators at the industry level for each country, net sales (S), net property, plant&equipment (C), R&D expenditures (R) have been deflated using the GDP deflators of respective countries.

The stock of R&D capital has been built on the basis of the permanent inventory method with a depreciation rate of equal to 15 percent and an initial stock of R&D capital calculated by assuming a growth rate of R&D expenditure equal to 5 percent (see graph 5).

Graph 6. Stock of R&D in percentage.



The second source of information is the firm's patent applications (see table 6 – graph 7) across technological classes according to the International Patent Classification (IPC) as published in Jaffe, Hall, Trajtenberg's database (2001) on National Bureau of Economic Research (NBER) website.

The authors have developed this datafile from US Patent&Trademark Office (USPTO) over January 1, 1963 – December 30, 1999.

The 2–digit IPC classification allow one to identify the technological classes of patent applications.

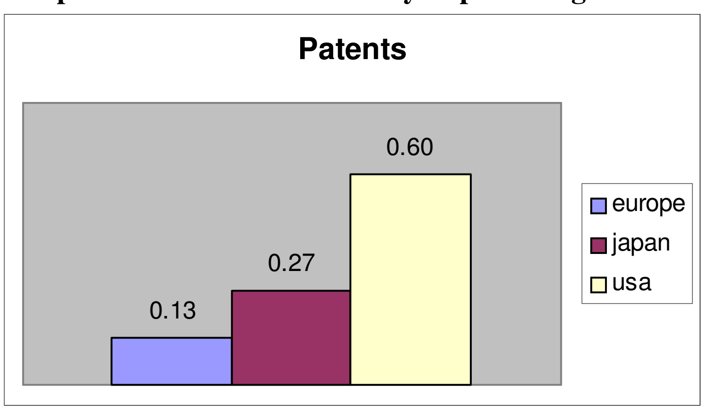
In particular, we identify 36 technological classes.

On this basis, a table of contigency, i.e. a table reporting the distribution of the firm's patents across the 36 IPC classes has been constructed in order to compute the index of technological proximity and consequently the stock of spillovers.

Table 6. Patents across country

Patent Applicant's country	Number of Patents	%
Europe	77211	0.13
Japan	156149	0.27
Usa	346705	0.60
Totals	580065	

Graph 7. Patents across country in percentage.



A third source of information is geographic coordinates of firm's countries. We can compute the geographic distance (in miles) among the firms from the latitude and the longitude (own calculations) of their countries.

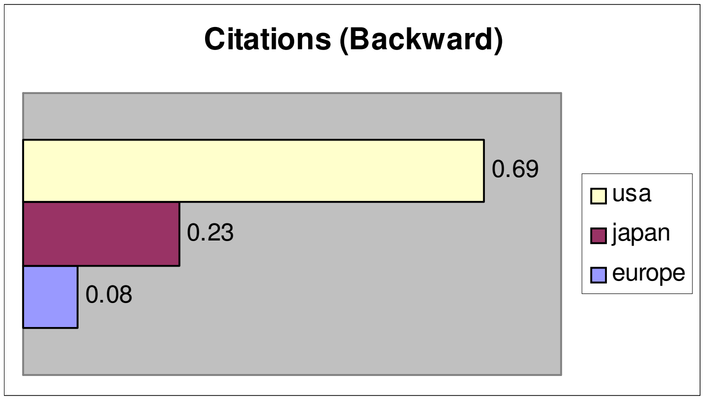
By assuming that the spillover effect is negatively correlated to the geographic distance, we use the Negative Exponential Function (NEF) to define a geographic proximity among the firms. So, we can construct the stock of spillovers.

Finally, we analyse the patent citations data from Jaffe, Hall, Trajtenberg' s datafile (NBER) to construct an asymmetric measure of proximity among the firms (see table 7 – graph 8).

Table 7. Citations (Backward) across country.

Citing country	**Number of citations**	**%**
Europe	115970	0.08
Japan	333468	0.23
Usa	981180	0.69
Total	1430618	

Graph 8. Citations across country in percentage.



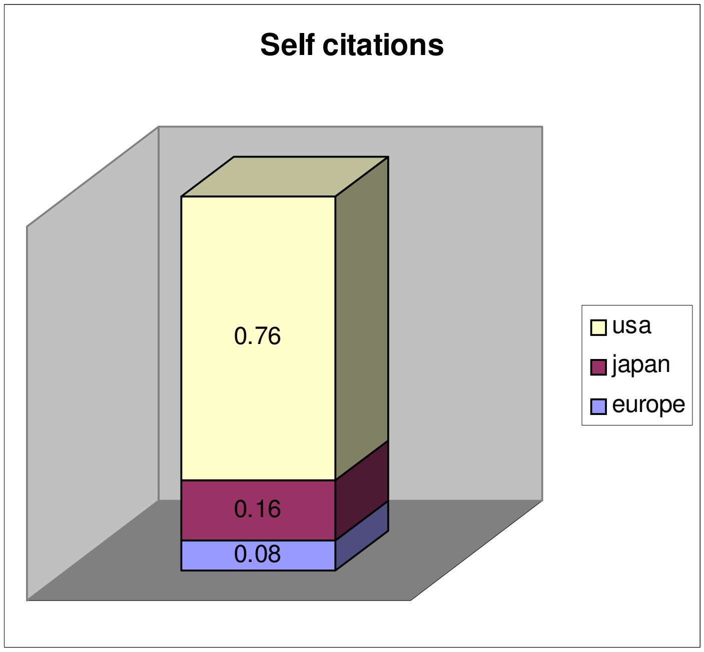
A strategic component of citations is the number of *self-citations.* They are used to investigate the role of prior R&D experience in enhancing a country's ability to understand and improve upon external knowledge (absorptive capacity).

In graph 9, we show the self-citations across country in percentage respect to total of self citations in the sample.

Table 8. Self citations across country

Patent Applicant's country	Number of self citations	%
Europe	45996	0.08
Japan	90284	0.16
Usa	432717	0.76
Total	568997	

Graph 9. Self citations across country in percentage



Finally, we define the following variables and in the table 9 we show the summary statistics for the sample (the variables are taken in natural logarithm values):

Ts=total stock of technological spillovers

Ns=national stock of technological spillovers

Is=international stock of technological spillovers

Tsg=total stock of geographic spillovers

Nsg=national stock of geographic spillovers

Isg=international stock of geographic spillovers

Tc=total stock of spillovers based on citation data

Nc=national stock of spillovers based on citation data

Ic=international stock of spillovers based on citation data

Table 9. Summary statistics for the complete sample.

Variable	Obs.	Mean	Std. Dev.	Min	Max
LS*	9640	12.00069	2.583033	3.319716	18.93346
LC	9640	12.21146	2.137725	3.135494	18.61529
LL	9640	8.182988	1.748013	1.609438	13.56062
LK	9640	11.73324	2.005447	4.77538	17.61461
LTS	9640	18.81877	.6608561	14.01393	19.95102
LNS	9640	17.79232	.7263196	13.39233	19.08739
LIS	9640	18.34222	.6909899	12.65365	19.60082
LTSG	9640	19.19508	.2373961	18.09949	20.18144
LNSG	9640	18.99278	.3729165	17.79752	19.74798
LISG	9640	17.15383	.6166388	15.67832	19.56008
LTC	9640	13.21452	.1796242	12.81229	13.56326
LNC	9640	12.48799	.1591573	11.89184	12.75621
LIC	9640	12.53635	.2709424	12.09268	13.03105
SELF	9640	.2078253	.2155917	0	1

*constant 1995 dollars.

3.2 Productivity equations and Econometric framework.

The R&D activity carried out by firms is expected to stimulate their productivity. Besides the impact of the firm's own R&D capital as well as the influence of labour and of the physical capital stock on productivity, it is worth examining to what extent the spillover stocks improve the firm's productivity. In order to investigate this question, an extended Cobb-Douglas production function[11] is used (Griliches, 1979). Formally, we have:

$$Yit = A_i \lambda_t L_{it}^{\beta_1} C_{it}^{\beta_2} K_{it}^{\beta_3} X_{it}^{\gamma} e^{\varepsilon_{it}}$$

[11] See chapter 2 for the procedure to construct the R&D capital stock (permanent inventory method).

where:

L_{it} is the employment of firm i at time t ,

K_{it} is the stock of R&D capital of firm i at time t,

Y_{it} is the net sales of firm i at time t,

C_{it} is the stock of physical capital,

A_i is the firm's specific effect,

λ_t is a set of time dummies,

X_{it} is a vector of spillover components of firm i at time t,

β, γ are the vector of parameters to estimate,

ε_{it} is a multiplicative disturbance term.

Usually, the previous equation is taken in logarithm to implement the estimation of the parameters. This leads to the following linear regression model:

$$\ln Yit \; = \; \alpha_i + \lambda_t + \beta_1 \ln C_{it} + \beta_2 \ln k_{it} + \beta_3 \ln L_{it} + \gamma \ln X_{it} + \varepsilon_{it}$$

where we consider the natural logarithm of the variables, in such way that we directly estimate the elasticity of net sales with respect to each input of the production function.

Following Capron and Cincera (1998), two interesting specifications of *Xit* have been considered:

- **Specification I:** impact of the total stock of spillovers

$$\gamma \ln X_{it} = \gamma_T \ TSit \qquad (24)$$

where: TS is the total stock of spillovers.

- **Specification II:** differentiated impact of the national and international spillover stocks

$$\gamma \ln X_{it} = \gamma_N \ln NS_{it} + \gamma_I \ln IS_{it} \qquad (25)$$

Given these formulations, the estimated coefficients associated with the spillover components can be interpreted as elasticities of output with respect to these components.

A standard approach to estimate these equations in the context of panel data, is to first-difference them to remove permanent unobserved heterogeneity and to use lagged levels of the series as instruments for the predertemined and endogenous variables in first-differences (GMM-IV F.D.).[12]

[12] See Anderson and Hsiao (1981), Holtz-Eeakin, Newey and Rosen (1988) and Arellano and Bond (1991).

3.3 Measuring the spillover components: technological proximity

A key issue in the empirical analysis on knowledge spillovers is the measurement of the pool of external knowledge. This is usually built as the amount of R&D conducted elsewhere weighted by some measure proximity in the technological or geographic space, taken to be representative of intensity of knowledge flows between the source and the recipient of spillovers.

Spillovers are believed to be higher between technological neighbors. According to this view, the ability to make productive use of another firm's knowledge depends on the degree of technological similarity between firms. Every technology has a somewhat unique set of applications and language. Researchers in similar technological fields will interact in professional organizations, publish in commonly read journals, and, increasingly, browse a common set of web pages. Reverse engineering may be employed to mantain parity with one's rivals. And spying and corporate espionage are thought to be relatively common among information intensive industries.

Different proximity measures have been used in the literature. A first one was employed by Bernstein, 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. The total unweighted stock of R&D spillovers (*TUi*) is computed as follows:

$$TU_i = R\_i - R_i \qquad (26)$$

where R_i is the total amount of R&D performed in i industry, and Ri is firm's i own R&D expenditure.

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 capture spurious effects due to common industry trends and shocks.

A more complex and commonly used measure of technological proximity was the one introduced by Jaffe (1986). In this chapter, we follow this methodology in computing the technologial proximity. According to this procedure, each firm is associated to a vector describing the distribution of its patents across technology classes. Such vector represents the firm's location in multi-dimensional technology space. Proximity between two firms is then obtained as the uncentered correlation coefficient between the corresponding location vectors.

According to this procedure, the total weighted stock of R&D spillovers has performed as follows:

$$TS_i = \sum_{i \neq j} P_{ij} K_j \quad (27)$$

where *Pij* is the technological proximity between firm *i* and *j*, *Kj* is firm's *j* R&D capital.

In particular,

$$P_{ij} = \frac{\sum_{k=1}^{K} T_{ik} T_{jk}}{\sqrt{\sum_{k=1}^{K} T_{ik}^{2} \sum_{k=1}^{K} T_{jk}^{2}}} \quad (28)$$

where *T* is the vector of technological position, regarding *K* industries.

In table 10, we show an example of technological proximity among five firms (Basf, Bayer, Hitachi Ltd, International Business Machine Corp (IB), Motorola) from our sample data:

Table 10. Technological proximities

	Basf	**Bayer**	**Hitachi LTD**	**IB**	**Motorola**
Basf	1.00	0.97	0.13	0.09	0.04
Bayer	0.97	1.00	0.08	0.05	0.02
Hitachi LTD	0.13	0.08	1.00	0.88	0.66
IB	0.09	0.05	0.88	1.00	0.61
Motorola	0.04	0.02	0.66	0.61	1.00

The index of technological distance relies on the strong assumption that the appropriability conditions of knowledge are the same for all firms (Jaffe, 1988). The more the outcomes of R&D activities are appropriable, the less there will be flows of knowledge between R&D performers and the potential users of this knowledge. In estimating the spillover effects, one would adding industrial or technologically narrowly defined sector dummies. Since these variables are not observable at the firm level, their direct assessment is hard to pick up. In panel data context, in order to attenuate this matter, one may assume that these firms specific unobserved effects are constant over the period considered.

The question of whether firm's position into the technological space is fixed or not is another issue which is empirically difficult to verify. Indeed, firms' R&D activities evolve over time, so does their technological position. However, there is reason to claim that over a short time period the firms' position in the technological space is to be fixed.

Another drawback of this procedure is that the uncentered correlation index for measuring technological proximities is a symmetric index. The technological proximity of firm A and firm B is the same than the one between the firm B and firm A. It would be interesting to use an asymmetrical index so one could separate the ability of firm A in capturing benefits from firm B'R&D from the one of firm B. Indeed, large and diversified firms have relative advantages in appropriating results from outside R&D.

One alternative to Jaffe's procedure is to use Euclidean distance between technological vectors endpoints. But this measure depends on the technological vector's length. The more the firms are diversified, the lesser the length of their technological vectors will be. They will be close each other even if their technological vectors are orthogonal, because they will be located in a central region of the technological space. The uncentered correlation coefficient is independent of technological vectors' length.

A second possibility is to depart from the uncentered correlation proximity measure and apply some transformations to it. Suppose that the technological distance is $Pij = 0.5$. We could investigate whether firms benefit more or much less from R&D spillovers than firms at the extreme, i.e. firms very close or very distant from other firms by assuming that the technological distance of firms is a multiplicative function of the *Pij*. Another possible transformation is to look at the logarithmic reciprocal function. Formally, the transformed *Pij* lead to the following formulation:

$$P_{ij}* = P_{ij}^{\varphi} \quad (29)$$

for the multiplicative function, and

$$P_{ij}** = \exp\left(\phi * \left(1 - \frac{1}{P_{ij}}\right)\right) \quad (30)$$

for the reciprocal logarithmic one.

The shapes characterizing these transformed proximity measures depend on the parameters ϕ and φ of the reciprocal logarithmic and multiplicative functions. The different proximity measures can be tested by letting the parameter of each function vary over a range of values and see what happens, from a statistical point of view, i.e. in terms of the regression's overall fit and estimated standard errors associated with the estimated spillover variables[13].

[13] See Cincera (1998) for a detailed description of the different methodologies to measure the technological proximity among the firms.

3.4 Empirical results: spillover effects.

Table 11 shows the econometric estimates[14], by first-differenced GMM, of spillover effects of R&D capital stock.

The elasticity of net sales with respect to physical capital is about 0.5 for all countries, while the elasticity of net sales with respect to labour is about 0.7 for US firms, about 1 for Japanese ones and about 0.5 for European ones.

As far as the R&D stock is concerned, its coefficient is about 0.1 for US and Japanese firms, and about 0.05 for European ones.

The elasticity of net sales with respect to total stock of spillovers is very high for US firms, almost 1 (0.92), high for Japanese ones (0.70) and positive but less than 0.5 for European ones (0.24). This result indicates some problem to face outside competitive threat for European firms.

Finally, in table 11 we take directly into account the geographic dimension of the dataset. Results of the effects of national and international stocks of R&D spillovers on net sales are performed for the US, Japan and Europe separately. We can observe that the US firms benefit principally from their national stock of spillovers, while Japan and Europe are more sensitive towards international ones. This fact makes USA a "leader" country in the innovation process.

[14] For all econometric estimates in this research, I use DPD98 in GAUSS, as software.

Table 11. Spillover effects (technological proximity).

DEPENDENT VARIABLE LN S					
GMM-IV F.D.					
SAMPLE: 964 FIRMS X 10 YEARS					
Δ ln C	0.59*	(0.033)			
Δ ln L	0.68*	(0.035)			
Δ ln K	-0.14	(0.019)			
Δ ln TS	0.70*	(0.037)			
X^2 (d.f.)	927.61	(80)			
US SAMPLE: 545 FIRMS X 10 YEARS					
Δ ln C	0.56*	(0.034)	Δ ln C	0.49*	(0.032)
Δ ln L	0.77*	(0.040)	Δ ln L	0.77*	(0.036)
Δ ln K	0.09**	(0.028)	Δ ln K	0.09**	(0.028)
Δ ln TS	0.92*	(0.041)	Δ ln NS	0.66*	(0.100)
			Δ ln IS	0.30*	(0.088)
X^2 (d.f.)	417.86	(80)	X^2 (d.f.)	518.40	(116)
JP SAMPLE: 288 FIRMS X 10 YEARS					
Δ ln C	0.38*	(0.067)	Δ ln C	0.48*	(0.054)
Δ ln L	1.26*	(0.063)	Δ ln L	0.96*	(0.049)
Δ ln K	0.07**	(0.037)	Δ ln K	0.07**	(0.037)
Δ ln TS	0.69*	(0.079)	Δ ln NS	1.08*	(0.178)
			Δ ln IS	- 0.51*	(0.190)
X^2 (d.f.)	767.14	(80)	X^2 (d.f.)	1124.54	(116)
EU SAMPLE: 131 FIRMS X 10 YEARS					
Δ ln C	0.57*	(0.059)	Δ ln C	0.51*	(0.055)
Δ ln L	0.51*	(0.063)	Δ ln L	0.53*	(0.059)
Δ ln K	0.04**	(0.043)	Δ ln K	0.04**	(0.043)
Δ ln TS	0.24*	(0.105)	Δ ln NS	- 0.23	(0.122)
			Δ ln IS	0.52*	(0.130)
X^2 (d.f.)	548.08	(91)	X^2 (d.f.)	595.75	(116)

Notes:
*(**)=statistically significant at the 5 (10)% level;
Heterosckedastic-consistent standard errors in brackets;
Instruments used: observations dated t-2, t-3 for the total sample, US sample, JP sample and t-2, t-3, t-4, t-5 for EU sample.
X^2 (d.f.) Sargan overidentification test (Sargan test) and number of degrees of freedom in brackets.

4. Geographical proximity based approach.

4.1 Measuring the spillover components: geographical proximity

Firms that are geographic neighbors may exchange knowledge through a variety of channels. Knowledge may be transmitted through employee interaction in social, civic and professional organizations, partecipation in which may be geographically constrained. Normal employee turnover can result in significant cross-pollination of knowledge stocks. And geographically near firms are likely to share buyers and suppliers who also may serve as conduits for information flow. Knowledge, sensitive to geographic distance, is defined also "tacit" or non-codified knowledge, because it refers to ideas not perfectly codified, but embodied in people.

To identify a geographical proximity measure there exist different techniques.

According to one methodology, each firm of the sample is to be located into a multi-dimensional space. To this end, each firm is assumed to exist at the geographic centroid of the county location of its corporate headquarters. A circle is effectively drawn around each firm and all other firms that fall inside the circle are defined geographically near; the remaining firms are defined as geographically distant.

Specifically, each firm's geographic location is defined with the state and county name. Each observation in the dataset reports the latitude and the longitude of the geographic centroid of a county in degrees, minutes, and seconds. The distance between any two firms in a given year is then computed as the distance between their respective county centroids. Assuming a spherical earth of actual earth volume, the arc distance in miles between any two firms *i* and *j* can be derived as:

$$d_{ij} = 2 * 3{,}959 * \arcsin \sqrt{\sin^2\left(\frac{lat_j - lat_i}{2}\right) + \left(\frac{\cos(lat_j) + \cos(lat_i)}{2} \sin\left(\frac{lon_j - lon_i}{2}\right)\right)^2} \quad (31)$$

where 3.959 is the radius of the earth in miles; latitude and longitude values are in radians.

Use of corporate headquarters to represent firm location may be questionable for the purpose of spillover detection. One may argue that our true interest is in the location of innovation, not necessarily in the location of corporate headquarters. However, if firms view R&D as their most strategically important investment they are likely to locate this activity close to corporate headquarters.

Furthermore, while R&D may be a reasonable proxy of the scale of a firm's innovative activity, spillovers from this implied knowledge base may emerge from any of the locations that compose the firm: R&D facilities, production facilities, or corporate headquarters. Thus, corporate headquarters may be as a good proxy of firm location.

The Directory of American Research and Technology 1993 was consulted to establish the reasonableness of the claim that corporate headquarters may be useful proxy for the source location of R&D spillovers.

Another way to take into account the geographic space is to consider the following model:

$$\Delta A_i = (R \,\&\, D)_i^a \, A_i^b \prod_{i \neq j} A_j^{c(dist_{ij})} \qquad (32)$$

where $\Delta A\, i$ represents the change over the considered period of the stock of knowledge originated in region i . Expression (32) says that innovation in region *i* depends on the Cobb-Douglas combination R&D resources used in region *i*, and on ideas available to the region at the beginning of the period. The elasticity of innovation to R&D resources is measured by *a.* Ideas generated in region *i*, enter with elasticity *b*, while ideas generated in other regions enter with elasticity *c* that depends on the distance in kilometres between region *i* and region *j*. In particular, one may assume that embodied knowledge does not diffuse passed a maximum distance *K*, and that its impact depends on the distance between regions as a step function. Hence the function *c(dist)* is equal to c_k / n_{ik} for $dist_{ij} \in K$, with $K = \{(dist_0, dist_1), (dist_1, dist_2), \ldots\ldots (K, \infty)\}$. The index *K* captures a sequence of distance intervals within which the step function is constant and n_{ik} is the total number of regions in the distance-interval k from region *i*. The assumption of no diffusion beyond distance *K* implies $c(k, \infty) = 0$. The specified diffusion process implies that innovation in region *i* depends on the average stock of ideas generated in regions within the distance-interval *K* with different sensitivities *c* for different distance-intervals.

Here, we follow Orlando's procedure (2000), but with a technical difference.

Orlando (2000) considers only US firms and computes the unweighted sum of R&D capital stock of those firms within a specified radius (50-miles, for istance) as spillover pool for firms defined geographically near.

Here, we assume that the stock of spillovers is negatively correlated to the geographic distance (*d*) to implement a weighted sum of R&D capital stock. We cannot use the function 1/*d* to compute the proximity (*Pij*) because if the distance between the firm *i, j* *dij* is equal to zero, the function 1/*dij* is not definite. To solve this problem, we use the Negative Exponential Function $1/e^{dij}$, so if the distance is zero, the geographic proximity is 1 (maximum value possible).

$$Pij = 1 / e^{dij} \quad (33)$$

Once we have computed the geographic proximity (*Pij*) among the firms, we can construct the stock of spillovers based on it:

$$S_i = \sum_{i \neq j} P_{ij} K_j$$

In table 12, we show an example of geographic proximity among five firms (Basf, Bayer, Hitachi Ltd, International Business Machine Corp (IB), Motorola) of our dataset:

Table 12. Geographical proximities

	Basf	**Bayer**	**Hitachi LTD**	**IB**	**Motorola**
Basf	1.00	0.91	0.00	0.04	0.02
Bayer	0.91	1.00	0.00	0.04	0.02
Hitachi LTD	0.00	0.00	1.00	0.03	0.06
IB	0.04	0.04	0.03	1.00	0.48
Motorola	0.02	0.02	0.06	0.48	1.00

Although the proximities based on the technological or geographic space are less likely to be contaminated by pecuniary externalities and common industry effects, evidence of its positive impact on productivity may still be unrelated to knowledge spillovers, but rather the result of spatially correlated technological opportunities. According to Griliches (1996), if new opportunities exogenously arise in a technological area, firms active in that area will increase their R&D spending and improve their productivity.

4.2 Empirical results: spillover effects.

We perform econometric estimates, by first-differenced GMM, by using dataset described in chapter 3.

Table 13 shows the empirical results of spillover effects of R&D capital stock.

The elasticity of net sales with respect to physical capital is about 0.6 for all countries, while the elasticity of net sales with respect to labour is about 0.6 for US and European firms, more than 1 for Japanese ones (1.31).

As far as the R&D stock is concerned, its coefficient is about 0.1 for US and Japanese firms, and about 0.05 for European ones.

The elasticity of net sales with respect to total stock of spillovers is high for US firms (0.6), and positive but less than 0.5 for Japanese and European ones (0.3). This result indicates some problem to face outside competitive threat for Japanese and European firms.

Finally, in table 13 we take directly into account the geographic dimension of the dataset. Results of the effects of national and international stocks of R&D spillovers on net sales are performed for the US, Japan and Europe separately. We can observe that all countries benefit principally from their national stock of spillovers. This fact indicates that the spillover effects are localised.

Table 13. Spillover effects (geographical proximity).

DEPENDENT VARIABLE LN S					
GMM-IV F.D.					
SAMPLE: 964 FIRMS X 10 YEARS					
Δ ln C	0.81*	(0.029)			
Δ ln L	0.48*	(0.032)			
Δ ln K	-0.11	(0.021)			
Δ ln TSG	0.36*	(0.023)			
X^2 (d.f.)	927.19	(80)			
US SAMPLE: 545 FIRMS X 10 YEARS					
Δ ln C	0.68*	(0.033)	Δ ln C	0.51*	(0.032)
Δ ln L	0.56*	(0.037)	Δ ln L	0.71*	(0.036)
Δ ln K	0.09**	(0.028)	Δ ln K	0.09**	(0.028)
Δ ln TSG	0.58*	(0.030)	Δ ln NSG	0.82*	(0.036)
			Δ ln ISG	0.00	(0.012)
X^2 (d.f.)	547.33	(80)	X^2 (d.f.)	515.55	(94)
JP SAMPLE: 288 FIRMS X 10 YEARS					
Δ ln C	0.57*	(0.055)	Δ ln C	0.62*	(0.065)
Δ ln L	1.31*	(0.069)	Δ ln L	1.25*	(0.071)
Δ ln K	0.07**	(0.037)	Δ ln K	0.07**	(0.037)
Δ ln TSG	0.34*	(0.047)	Δ ln NSG	0.28*	(0.050)
			Δ ln ISG	0.00	(0.064)
X^2 (d.f.)	698.43	(80)	X^2 (d.f.)	747.22	(94)
EU SAMPLE: 131 FIRMS X 10 YEARS					
Δ ln C	0.54*	(0.044)	Δ ln C	0.38*	(0.057)
Δ ln L	0.58*	(0.037)	Δ ln L	0.70*	(0.061)
Δ ln K	0.04**	(0.042)	Δ ln K	0.04**	(0.042)
Δ ln TSG	0.33*	(0.069)	Δ ln NSG	0.52*	(0.094)
			Δ ln ISG	-0.02	(0.011)
X^2 (d.f.)	495.37	(94)	X^2 (d.f.)	620.37	(94)

Notes:
*(**)=statistically significant at the 5 (10)% level;
Heterosckedastic-consistent standard errors in brackets;
Instruments used: observations dated t-2, t-3 for the total sample, US sample, JP sample and t-2, t-3, t-4, t-5 for EU sample.
X^2 (d.f.) Sargan overidentification test (Sargan test) and number of degrees of freedom in brackets.

4.3 General analysis: technological and geographical proximity based simultaneous approach.

In table 14, we run a simultaneous econometric analysis. In fact, we consider together the effects of R&D spillover stocks based on technological proximity and those based on geographical one.

The effect of total stock of spillovers on net sales is significantly positive in both cases, but it is stronger in technological proximity case. We can see that this effect for Europe is weaker.

USA and Japanese firms benefit mainly for national stock of both spillovers while European firms benefit from national stock of geographic spillovers and from international stock of technological spillovers.

Table 14. Spillover effects (technological and geographical proximity).

DEPENDENT VARIABLE LN S					
GMM-IV F.D.					
US SAMPLE: 545 FIRMS X 10 YEARS					
Δ ln C	0.54*	(0.045)	Δ ln C	0.31*	(0.023)
Δ ln L	0.67*	(0.067)	Δ ln L	0.75*	(0.036)
Δ ln K	0.09**	(0.028)	Δ ln K	0.09**	(0.028)
Δ ln TS	0.64*	(0.070)	Δ ln NS	0.44*	(0.080)
Δ ln TSG	0.15*	(0.030)	Δ ln IS	- 0.14	(0.086)
			Δ ln NSG	0.59*	(0.077)
			Δ ln ISG	0.00	(0.006)
X^2 (d.f.)	191.16	(94)	X^2 (d.f.)	297.65	(199)
JP SAMPLE: 288 FIRMS X 10 YEARS					
Δ ln C	0.37*	(0.043)	Δ ln C	0.36*	(0.014)
Δ ln L	1.23*	(0.070)	Δ ln L	0.03*	(0.013)
Δ ln K	0.07**	(0.037)	Δ ln K	0.07**	(0.037)
Δ ln TS	0.58*	(0.070)	Δ ln NS	4.45*	(0.082)
Δ ln TSG	0.12*	(0.020)	Δ ln IS	0.19*	(0.078)
			Δ ln NSG	0.17*	(0.003)
X^2 (d.f.)	252.60	(94)	Δ ln ISG	- 2.91*	(0.039)
			X^2 (d.f.)	247.74	(199)
EU SAMPLE: 131 FIRMS X 10 YEARS					
Δ ln C	0.66*	(0.025)	Δ ln C	0.37*	(0.012)
Δ ln L	0.41*	(0.031)	Δ ln L	0.66*	(0.010)
Δ ln K	0.04**	(0.042)	Δ ln K	0.04**	(0.042)
Δ ln TS	0.16*	(0.053)	Δ ln NS	-0.47*	(0.035)
Δ ln TSG	-0.06*	(0.020)	Δ ln IS	0.01*	(0.041)
			Δ ln NSG	0.92*	(0.043)
X^2 (d.f.)	124.93	(94)	Δ ln ISG	-0.02*	(0.001)
			X^2 (d.f.)	129.32	(122)

Notes:
*(**)=statistically significant at the 5 (10)% level;
Heterosckedastic-consistent standard errors in brackets;
Instruments used: observations dated t-2, t-3 for the total sample, US sample, JP sample and t-2, t-3, t-4, t-5 for EU sample.

X^2 (d.f.) Sargan overidentification test (Sargan test) and number of degrees of freedom in brackets.

5. An asymmetrical measure from patent citations data.

5.1 Patent citations data characteristics.

Econometric studies of technological change have traditionally relied heavily on patent as indicators of innovation activity. As well explained by Griliches' (1990) classic survey, patent data are easily available, cover many countries, and are rich of technical information, thanks to their fine classification. The US Patent&Trademark Office (USPTO) and, from the 1980s, the European Patent Office (EPO) are the most heavily exploited sources.

In the past 15 years or so, traditional patent counts (and the related statistics on countries' and firms' patent shares) have been increasingly complemented with the analysis of patent citations mainly for one reason. The citations have been interpreted as "paper trails" left by knowledge flowing from the inventor or applicant of the cited document to the inventor/applicant of the citing one.

Nevertheless, like other technological indicators, patent statistics have their own weaknesses. The same weight given to patents by simply counting them is an important drawback of this indicator. Actually, the pure technical content as well as the intrinsic economic value of a patent may vary widely among patents. Not all inventions are patented, nor all are patentable, and other existing methods in appropriating an innovation such as industrial secrecy may be preferred. The propensity to patent may change substantially over time and across countries not to mention among technological sectors. For example, it is generally recognized that the propensity to patent is important in sectors such as machinery or chemicals but very weak in aerospace and in software since in the latter industries innovation are more easy to copy.

Most studies consider patent statistics coming from the US Patent Office. This office has often been described as the most adequate since the United States is the most important market for inventions at the international level. Yet, a methodological issue, when using patent statistics as technological indicator, is their comparability at the international level. For instance, patenting regulations differ among different national and international patent offices and over time, making comparisons more difficult. Aggregate data suggest that Japanese and European firms apply for and obtain far fewer patent grants from US Patent Office than from their own domestic patent offices. Hence, using American patents to infer technological performances or technological proximities of Japanese and European firms may be quite distorted and incomplete. Hence, it would be interesting in the future to look at other patent offices and to see how much we are missing by considering American patents only.

Furthermore, many doubts exist whether patent citations really reflect the designated inventors' knowledge of both their technical fields, and of the other inventors and experts: citations, in fact, come mainly from the patent examiners, and possibly the patent applicant's lawyers, rather than from the inventors themselves. In addition, some confusion exists between the two issues of awareness (whether citing inventors actually knew of the cited patents), and existence of a knowledge flow (whether some information on the contents of the cited patents has however reached the, possibly unaware, citing inventor). In order to deal with these matters, Breschi and Lissoni (2004) apply a social network analysis to derive maps of social relationships between inventors, and measures of social proximity between citing and cited patents. In particular, they introduce the concept of geodesic distance as social proximity between patents. Let us suppose we face three patent applications (1 to 3), which are produced by four different inventors (A, B, C, D). We can reasonably assume that, due to the collaboration in a common research project, the four inventors are linked to each other by some kind of knowledge relation. Suppose also that A,B have colloborated in 1, B,C in 2 and C,D in 3. The geodesic distance is defined as the minimum number of steps (or more formally edges) that separate two distinct inventors in the network. For example, A and B have geodesic distance equal to 1, whereas inventors A and C have distance 2 and inventors A and D have distance 3. Even though inventor A does not know directly inventor D, he knows who (inventor B) knows who (inventor C) knows direcly inventor D. By logit regressions, Breschi and Lissoni (2004) demonstrate that the probability to observe a citation is influenced by such geodesic distance. They found also that, in the absence of social connectedness, geographical proximity can hardly explain citation patterns; on the contrary, social connectedness enhances the role of geographical proximity, especially when the social distance between inventors is short.

In this research, I focus on the construction of an asymmetric proximity to measure the distance between two firms. To this end, I suppose that social connectedness exists and that the geodesic distance between citing and cited patents are not very long. But in the future, it would be interesting to investigate the social network of patent citations data, to delete those citations characterized by absence of social connectedness with respect to other patents in the database, and to analyse how this procedure affects the final econometric results.

5.2 Measuring the spillover components: an asymmetric proximity.

Usually, citation data are used in probit and logit models to estimate the probability a citation happens. Here, we use them in an extended production function approach.

We construct an asymmetric proximity among the firms. In particular, we get:

$$P_{ij} = \frac{C_{ij}}{Ci.} \quad (34)$$

where *Cij* = Number of citations from firm *i* to firm *j;*

Ci. = Total number of citations of firm *i.*

Also in this case the proximity *Pij* takes values between one and zero.

Once we have computed the citation proximities among the firms, we get the following stock of spillovers:

$$S_i = \sum_{i \neq j} P_{ij} K_j$$

In table 15, we show an example of citation proximity among five firms (Basf, Bayer, Hitachi Ltd, International Business Machine Corp (IB), Motorola):

Table 15. Citation proximities

	Basf**	Bayer	Hitachi LTD	IB	Motorola
Basf*	0.390	0.090	0.003	0.010	0.000
Bayer	0.040	0.526	0.001	0.001	0.003
Hitachi LTD	0.001	0.001	0.277	0.128	0.027
IB	0.001	0.001	0.059	0.413	0.035
Motorola	0.000	0.000	0.042	0.081	0.379

*citing firms; **cited firms

The elements of principal diagonal indicate the self-citations proximities.

Table 16. Matrix of knowledge flows in percentage across country based on citation data and as average among the firms.

	eu[15]	jap	usa	self	tot
eu[16]	0.10	0.14	0.36	0.40	1.00
jap	0.05	0.32	0.35	0.27	1.00
usa	0.05	0.13	0.37	0.44	1.00

Table 16 reports the directions of citations, for all countries in the sample, and their relative weights. In particular, 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). Most of the citations are to patents held by American firms.

[15] Cited country.
[16] Citing country.

5.3.1 Empirical results: spillover effects.

We perform econometric estimates, by first-differenced GMM, by using dataset described in chapter 3.

Table 17 shows the empirical results of spillover effects of R&D capital stock.

The elasticity of net sales with respect to physical capital is about 0.5 for all countries, while the elasticity of net sales with respect to labour is about 0.7 for US and European firms, more than 1 for Japanese ones (1.32).

As far as the R&D stock is concerned, its coefficient is about 0.1 for US and Japanese firms, and about 0.05 for European ones.

The elasticity of net sales with respect to total stock of spillovers is very high for US firms, almost 1 (0.91), high for Japanese ones (0.63) and positive but less than 0.5 for European ones (0.44). This result indicates some problem to face outside competitive threat for European firms.

Finally, in table 16 we take directly into account the geographic dimension of the dataset. Results of the effects of national and international stocks of R&D spillovers on net sales are performed for the US, Japan and Europe separately. We can observe that the US and Japanese firms benefit principally from their national stock of spillovers, while Europe are more sensitive towards international ones.

In the previous chapters, we have considered two dimensions of spillovers: technological and geographical. Both techniques lead us to a positive effect of total stock of spillovers on firms sales. According to the technological proximity based approach US and Japanese firms benefit more from domestic stock of spillovers, while European ones benefit more from international stock of spillovers. Differently, according to the geographical proximity based approach, all firms benefit more from national stock of spillovers.

In this chapter we have used a proximity based on the patent citations. The new approach estimates confirm those of technological approach.

Furthermore, in order to explain economically the empirical results, we can move towards two directions. Recall that the total effect of spillovers is equal to an indirect innovative effect (positive) minus a strategic effect (negative) due to the outside competitive activities of the firms. Thus, in the following section we analyse the absorptive capacity of the firms, which influences the innovative effects of spillovers, while in the final section of the chapter, we analyse the strategic effects of spillovers through the market shares of the firms.

Table 17. Spillover effects (patent citations proximity).

DEPENDENT VARIABLE LN S					
GMM-IV F.D.					
SAMPLE: 964 FIRMS X 10 YEARS					
Δ ln C	0.41*	(0.034)			
Δ ln L	0.93*	(0.036)			
Δ ln K	-0.14	(0.027)			
Δ ln TC	0.84*	(0.035)			
X^2 (d.f.)	1253.48	(80)			
US SAMPLE: 545 FIRMS X 10 YEARS					
Δ ln C	0.51*	(0.034)	Δ ln C	0.43*	(0.034)
Δ ln L	0.79*	(0.039)	Δ ln L	0.78*	(0.038)
Δ ln K	0.09**	(0.037)	Δ ln K	0.09**	(0.037)
Δ ln TC	0.91*	(0.037)	Δ ln NC	1.91*	(0.212)
			Δ ln IC	-0.94*	(0.203)
X^2 (d.f.)	411.55	(80)	X^2 (d.f.)	416.92	(80)
JP SAMPLE: 288 FIRMS X 10 YEARS					
Δ ln C	0.37*	(0.069)	Δ ln C	0.40*	(0.049)
Δ ln L	1.32*	(0.067)	Δ ln L	0.57*	(0.065)
Δ ln K	0.07**	(0.027)	Δ ln K	0.07**	(0.027)
Δ ln TC	0.63*	(0.073)	Δ ln NC	7.29*	(0.413)
			Δ ln IC	-6.71	(0.415)
X^2 (d.f.)	708.67	(80)	X^2 (d.f.)	1085.77	(80)
EU SAMPLE: 131 FIRMS X 10 YEARS					
Δ ln C	0.46*	(0.063)	Δ ln C	0.48*	(0.063)
Δ ln L	0.65*	(0.068)	Δ ln L	0.64*	(0.067)
Δ ln K	0.04**	(0.037)	Δ ln K	0.04**	(0.037)
Δ ln TC	0.44*	(0.104)	Δ ln NC	-3.01*	(0.506)
			Δ ln IC	3.45*	(0.504)
X^2 (d.f.)	531.64	(80)	X^2 (d.f.)	482.83	(80)

Notes:
*(**)=statistically significant at the 5 (10)% level;
Heterosckedastic-consistent standard errors in brackets;
Instruments used: observations dated t-2, t-3 for the total sample, US sample, JP sample and t-2, t-3, t-4, t-5 for EU sample.
X^2 (d.f.) Sargan overidentification test (Sargan test) and number of degrees of freedom in brackets.

5.3.2 Empirical results: Absorptive capacity level.

In order to pick up the firms' ability to identify, assimilate and exploit outside innovation (absorptive capacity), which depends on the level of knowledge accumulated by the firms, we follow two methodologies: traditional one, which is based on Cohen and Levinthal's idea. We construct a variable, KTC, which is an interaction term between the own R&D capital stock and the total stock of R&D spillovers; and innovative one, which considers a variable, STC, an interaction term between the self-citations and the total stock of R&D spillovers.

From econometric results of table 18, we learn that, in both cases, US firms have a good level of knowledge, Japanese firms are working to reach it, while European ones has to engage more in R&D investments, because they suffer from outside competitive innovation.

Table 18. Absorptive capacity effect

DEPENDENT VARIABLE LN S					
GMM-IV F.D.					
US SAMPLE: 545 FIRMS X 10 YEARS			US SAMPLE: 545 FIRMS X 10 YEARS		
Δ ln C	0.35*	(0.034)	Δ ln C	0.80*	(0.032)
Δ ln L	0.95*	(0.037)	Δ ln L	0.37*	(0.032)
Δ ln K	0.14*	(0.025)	Δ ln K	0.14*	(0.025)
Δ ln KTC	0.09*	(0.074)	Δ ln STC	0.49*	(0.074)
X^2 (d.f.)	416.94	(103)	X^2 (d.f.)	874.76	(92)
JP SAMPLE: 288 FIRMS X 10 YEARS			JP SAMPLE: 288 FIRMS X 10 YEARS		
Δ ln C	0.36*	(0.055)	Δ ln C	0.60*	(0.036)
Δ ln L	1.10*	(0.058)	Δ ln L	1.12*	(0.064)
Δ ln K	0.06**	(0.036)	Δ ln K	0.06**	(0.036)
Δ ln KTC	0.05*	(0.006)	Δ ln STC	0.20**	(0.124)
X^2 (d.f.)	531.86	(103)	X^2 (d.f.)	971.81	(77)
EU SAMPLE: 131 FIRMS X 10 YEARS			EU SAMPLE: 131 FIRMS X 10 YEARS		
Δ ln C	0.74*	(0.037)	Δ ln C	0.74*	(0.037)
Δ ln L	0.44*	(0.034)	Δ ln L	0.44*	(0.034)
Δ ln K	0.05	(0.043)	Δ ln K	0.05	(0.043)
Δ ln KTC	0.03*	(0.006)	Δ ln STC	- 0.40*	(0.137)
X^2 (d.f.)	525.26	(103)	X^2 (d.f.)	425.51	(77)

Notes:
*(**)=statistically significant at the 5 (10)% level;
Heterosckedastic-consistent standard errors in brackets;
Instruments used: observations dated t-1, t-2, t-3 for US sample, t-1 for JP sample and EU sample.
X^2 (d.f.) Sargan overidentification test (Sargan test) and number of degrees of freedom in brackets.

5.3.3 Empirical results: market share effects.

"...monopolistic structure is more conducive to innovation in fields with a slow pace of scientific advances or limited opportunities for product differentiation whereas the effect of monopoly power is weak or even negative in high opportunity fields".

F. M. Scherer (1984).

We know that the total effects on net sales of R&D spillovers depend on two distint effects: a positive effect or innovative effect (positively correlated to the absorptive capacity) and a negative effect or strategic effect, due to competitive activities of the firms.

According to Schumpeterian view (see chapter 1), if innovative effect does not change, more a sector is concentrated (there are less firms), more the spillover effect is high, because the strategic effect goes down.

This concept is confirmed for European firms in table 19. Here, we have constructed a variable, QTC, which is an interaction term between the market shares, q, and the total stock of spillovers. In particular, q is equal to the ratio between the sales per year and per country of a firm and its total sales. The coefficient of this variable is positive and significative (0.71).

The structure of innovative process in USA is different. If a sector is more concentrated, the strategic effect goes down, but also the innovative effect suffer from this process. The final result could be negative, as we can observe for US firms (-2.65).

The coefficient of QTC is positive but not significative for Japanese firms. Thus, we cannot explain the market shares effects in Japan.

Table 19. market share effects.

DEPENDENT VARIABLE LN S		
GMM-IV F.D.		
US SAMPLE: 545 FIRMS X 10 YEARS		
Δ ln C	0.96*	(0.032)
Δ ln L	0.33*	(0.034)
Δ ln K	0.08*	(0.029)
Δ ln qTC	-2.65*	(0.782)
X^2 (d.f.)	698.64	(92)
JP SAMPLE: 288 FIRMS X 10 YEARS		
Δ ln C	0.63*	(0.033)
Δ ln L	1.06*	(0.061)
Δ ln K	0.07**	(0.035)
Δ ln qTC	1.42	(0.961)
X^2 (d.f.)	1034.08	(77)
EU SAMPLE: 131 FIRMS X 10 YEARS		
Δ ln C	0.67*	(0.033)
Δ ln L	0.45*	(0.030)
Δ ln K	0.07**	(0.041)
Δ ln qTC	0.71*	(0.365)
X^2 (d.f.)	522.44	(103)

Notes:
*(**)=statistically significant at the 5 (10)% level;
Heterosckedastic-consistent standard errors in brackets;
Instruments used: observations dated t-1, t-2, t-3 for US sample, t-1 for JP sample and t-1, t-2, t-3, t-4, t-5 for EU sample

X^2 (d.f.) Sargan overidentification test (Sargan test) and number of degrees of freedom in brackets.

6. CONCLUSIONS.

In this research, we have investigated the effects of R&D spillover effects on firms' economic performances as measured by net sales. To this end, a new database has been constructed. This database consists of 964 large international firms in the manufacturing sector over the period 1988-1997. This information is matched to the USPTO dataset of Hall, Jaffe and Trajtenberg (2001). Thanks to the international dimension of the database, it has been possible to compare the relative firms' performances across different geographic areas. The construction and the main features of this database has been discussed in chapter 3.

In chapter 1, we have discussed the main determinants and effects of technological change and we have addressed some issues concerning measurement.

In chapter 2, we have described the main theoretic models and their empirical evidence about the measurement of R&D spillovers and their effects on firms' productivity growth. In particular, we have described two alternative methodologies. It is possibile to implement a production function approach, in which one uses an extended Cobb-Douglas production function. In this case, the dependent variable is measured by firms' productivity growth (or net sales, as proxy). Or one can directly measure the effects of R&D spillovers on the innovation, measured by number of patents. In this case, a knowledge production function approach is implemented. Provided that the patents are count variable, one has to assume a particular probability distribution of error terms, such as Poisson distribution or the Negative Binomial distribution to perform the econometric estimates within knowledge production function approach. A standard approach to estimate an extended Cobb-Douglas production function in the context of panel data is to first-difference it to remove permanent unobserved heterogeneity and to use lagged levels of the series as instruments for the predetermined and endogenous variables in first-differences (GMM in F.D.). In this research, we follow a production function approach.

In order to construct the R&D spillover components, we could consider a technological or a geographical dimension, in the sense that the R&D capital stock of a firm can affect the sales of another firm because both firms are engaged in the same technological sectors, or because both firms are geographically near.

In chapter 3, we have assumed a technological proximity among the firms. The approach for modelling technology based R&D spillovers builds on the methodology first implemented by Jaffe (1986). This method rests on technological proximities between firms in a technological space. The firms' positions in the technological space are characterized by the distribution of their patents over patent classes.

In chapter 4, we have assumed a geographical proximity among the firms. Locational R&D spillovers rest on the geographical distances among firms which uses the latitude and longitude coordinates of corporate headquarters (Orlando, 2000). Firms falling inside a circle around the geographic centroid of the firm's location are defined as geographically near.

Both techniques lead us to a positive effect of total stock of spillovers on firms sales. According to the technological proximity based approach US and Japanese firms benefit more from domestic stock of spillovers, while European ones benefit more from international stock of spillovers. Differently, according to the geographical proximity based approach, all firms benefit more from national stock of spillovers.

In both cases, we have constructed a symmetric proximity among the firms.

In order to get an asymmetric proximity, in chapter 5 we use the patent citations. The new approach estimates confirm those of technological approach. Among technologically similar firms, the partial spillover enhancing effect of geographic proximity is much less significant. A defense of mergers between firms in a particular geographic region therefore may not be justified by the internalization of knowledge spillovers' argument.

In order to explain economically the empirical results, we can move towards two directions. Recall that the total effect of spillovers is equal to an indirect innovative effect (positive) minus a strategic effect (negative) due to the outside competitive activities of the firms. Thus, on one hand, in order to pick up the firms' ability to identify, assimilate and exploit outside innovation (absorptive capacity), which depends on the level of knowledge accumulated by the firms, we construct two variables which are an interaction term between the self-citations and the total stock of R&D spillovers, and an interaction term between the own R&D capital stock and the total stock of R&D spillovers. From econometric results, we learn that, in both cases, US firms have a good level of knowledge, Japanese firms are working to reach it, while European ones has to engage more in R&D investments, because they suffer from outside competitive innovation.

On the other hand, in the final section of chapter 5, we have anlysed the market share effects. To this end, we have constructed a new variable which is an interaction term between firms' market shares, measured as ratio between the firm's sales per year and per country and country's total sales, and total stock of R&D spillovers.

According to Schumpeterian view (see chapter 1), if innovative effect does not change, more a sector is concentrated (there are less firms), more the spillover effect is high, because the strategic effect goes down.

This concept is confirmed for European firms. The coefficient of interaction variable is positive and significative (0.71).

The structure of innovative process in USA is different. If a sector is more concentrated, the strategic effect goes down, but also the innovative effect suffer from this process. The final result could be negative, as we can observe for US firms (-2.65). The coefficient of the interaction variable is positive but not significative for Japanese firms. Thus, we cannot explain the market shares effects in Japan.

The finding that R&D spillovers are largest among firms in the same narrowly defined technological sector might support arguments in defense of increased concentration in particular sectors. But from the previous discussion, we learn that only follower firms can benefit from this strategy. Thus, in order to face well outside competitive activities, the best strategy is to accumulate a very high knowledge.

This research could be further extended by examining more precisely the time it takes to R&D spillover effects to show up on productivity growth, or by investigating the strategic effects of R&D spillovers in a micro sectorial analysis.

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