UNIVERSITÀ DEGLI STUDI DI NAPOLI
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ABSORPTIVE CAPACITY AND KNOWEDGE SPILLOVERS FOR LARGE INTERNATIONAL FIRMS: A SURVEY

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Abstract.
The main objective of this paper is that of surveying both theoretic and econometric models exploring the existence of knowledge spillovers and quantifying firm's ability to identify, assimilate, and exploit existing information (absorptive capacity). In order to construct the spillover stocks, different dimensions are considered: geographic and technological. In particular, our attention is focused on the recent works that have pioneered the use of patent citations as "paper trail" left by knowledge flowing between different companies and inventors.

Keywords: Absorptive Capacity, Knowledge Spillovers.

JEL codes: O33, O47

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Indice

1. INTRODUCTION

"…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)

According to the catching-up hypothesis, (Abramovitz, 1986), lower productivity levels lead to higher productivity growth rates. This feature is expected to be realized if a country is not technologically backward without qualification, but it is technologically backward and socially advanced[1].
The diffusion of knowledge regards international technical communication, multinational corporations, international trade and direct capital investments among different technological areas.
Cohen and Levinthal (1989) argue that Research and Development (R&D) investments have two targets: they generate new information (innovation process), and they enhance the firm's ability to identify, assimilate and exploit existing information (learning process or absorptive capacity).
A fundamental difference between the learning-by-doing process and the absorptive capacity is that in the former case, the production of the output becomes more efficient, through the repetition of the industrial process, while in the latter one, agents receive new ideas from outside to realize a new product.

ABSORPTIVE CAPACITY ↔OWN R&D→ TECHNOLOGICAL KNOWLEDGE
↓→→→→→ **SPILLOVERS**→→→→→↑

Technological knowledge is a public good, suggesting the existence of the indirect effects of own R&D capital on other firms productivity[2]; these effects are generally called spillovers (Griliches, 1992)[3].

Knowledge external to a production unit is a combination of R&D performed by other production units (firms, regions or countries) somehow weighted to account for the intensity of knowledge flows between the source and the destination.

Regardless of the way external knowledge has been measured its impact has been assessed mainly within two different frameworks: by introducing the chosen measure into an aggregate production

[1] Stern, Porter, Furman (2000) introduce the National Innovative Capacity concept to pick up the differences in R&D productivity across advanced economies: it is the ability of a country to produce and commercialise a flow of innovative technology over a long term.
[2] It is far from straightforward the different effects of public and private R&D capital. For instance, David, Hall, Toole (1999) show ambivalent results for them.
[3] In order to compute R&D spillover stocks, we can consider Jaffe's procedure (1986), based on the localization of firms in the technological space. Jaffe (1986) also show that spillovers have effects not only on firms productivity but also on profits.

function or into a knowledge production function. In the first case the aim is to assess the impact of spillovers on productivity, while in the second case their effect is measured directly on innovation.

The paper is organised as follows. Section 2 reviews the main approaches proposed in the literature to formalize the impact of R&D spillovers on firms' economic performance, while their empirical findings are summarised in the Section 3. Finally, Section 4 discusses some points deserving further research.

2. FRAMEWORK TO FORMALIZE R&D SPILLOVERS: A REVIEW OF THE LITERATURE

2.1. Technological and Geographic proximities

Knowledge externalities are realised into two steps. Knowledge flows represent the first step and take place whenever ideas generated by a firm or country are learned by another firm or country. Such learning creates a pool of accessible external knowledge, which has a positive effect on productivity, however measured (this is the second step).
Griliches (1979) identifies two sources of potential externalities generated by R&D activities: rent spillovers and pure knowledge spillovers. Rent spillovers arise when the prices of intermediate inputs purchased from other firms or countries are not fully adjusted for quality improvements resulting from R&D investment. As such, they originate from economic transactions and are the consequence of "measurement errors".
By contrast, pure knowledge spillovers arise because of the imperfect appropriability of ideas: the benefits of new knowledge accrue not only to the innovator, but "spill over" to other firms or countries, thus enriching the pool of ideas upon which subsequent innovations can be based. Hence knowledge spillovers may occur without any economic transactions and are not the manifestation of any measurement error.

Theoretically, the distinction between the two concepts of spillovers seems clear, but their empirical identification is rather more complex. One reason for this ambiguity is that economic transactions that originate rent spillovers may also imply some knowledge transfers[4].
Further difficulties arise because innovation by competitors may also generate strategic effects. If technological rivalry is strong and means of appropriation are effective, firms could find themselves engaged into a race for the appropriation of new profitable ideas. As a consequence, the positive technological externality arising from other firms' research can potentially be confounded with a negative effect due to the competition.

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.

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:

[4] As pointed out in Cincera and Van Pottelsberghe de la Potterie (2001), there are also other channels through which rent spillovers potentially operate: transaction in investment goods and the use by one firm or country of patents granted to other firms or countries.

$$TU_i = R\_i - R_i \qquad (1)$$

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). 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:

$$TS_i = \sum_{i \neq j} P_{ij} K_j \qquad (2)$$

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

$$P_{ij} = \frac{\sum_{k=1}^{K} T_{ik} T_{jk}}{\sqrt{\sum_{k=1}^{K} T_{ik}^2 \sum_{k=1}^{K} T_{jk}^2}} \qquad (3)$$

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

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:

$$P_{ij}* = P_{ij}^{\varphi} \quad (4)$$

for the multiplicative function, and

$$P_{ij}** = \exp\left(\phi * \left(1 - \frac{1}{P_{ij}}\right)\right) \quad (5)$$

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[5].

Also to identify a geographic 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:

$$d_{ij} = 2 * 3{,}959 * \arcsin\sqrt{\sin^2\left(\frac{lat_j - lat_i}{2}\right) + \left(\frac{\cos(lat_j) + \cos(lat_i)}{2}\sin\left(\frac{lon_j - lon_i}{2}\right)\right)^2} \quad (6)$$

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

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

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:

$$\Delta A_i = (R\,\&\,D)_i^a \, A_i^b \prod_{i \neq j} A_j^{c(dist_{ij})} \qquad (7)$$

where $\Delta A\,i$ represents the change over the considered period of the stock of knowledge originated in region i . Expression (7) 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. .

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. This would erroneously show up a spillover effect. In trying to avoid these problems the most recent studies have been using a new and potentially rich source of information represented by patent citations.

2.2 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:

$$\ln Yit \;=\; \alpha_i + \lambda_t + \beta_1 \ln C_{it} + \beta_2 \ln k_{it} + \beta_3 \ln L_{it} + \gamma \ln X_{it} + \varepsilon_{it} \qquad (8)$$

where: ln is the natural logarithm,
Lit is the employment of firm i at time t ,
Kit is the stock of R&D capital,
Yit is the value-added of firm i at time t,
Cit is the stock of physical capital,
αi is the firm's specific effect,
λt is a set of time dummies,
Xit is a vector of spillover components,
γ is its associated vector of parameters,
εit 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:

$$\begin{aligned} Kit \quad &= (1-\partial)K_{it-1} + R_{it} = \\ &= R_{it} + (1-\partial)R_{it-1} + (1-\partial)^2 R_{it-2} \dots = \\ &= \sum_{\tau=0}^{\infty} (1-\partial)^{\tau} R_{it-\tau} \end{aligned} \qquad (9)$$

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:*

$$k_{i0} = R_{i0} \sum_{\tau=0}^{\infty} \frac{(1-\partial)^{\tau}}{(1-g)} = \frac{R_{i0}}{(g+\partial)} \qquad (10)$$

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[6].
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-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:

$$\ln \mu_{it} = \alpha_i + \beta x_{it} \qquad (11)$$

[6] See Cincera (1998) for a deep analysis for most econometric techniques used for count data models.

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:

$$\prod_i \prod_t \left(\frac{\exp(\beta x_{it})}{\sum_s \exp(\beta x_{is})} \right)^{y_{it}} \qquad (12)$$

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} / γ_{it} ~ Poisson (γ_{it}) and γ_{it} / θ_i ~ Gamma (λ_{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:

$$f(y_{it} / \lambda_{it}, \theta_i) = \frac{\Gamma(\lambda_{it} + y_{it})}{\Gamma(\lambda_{it})\Gamma(y_{it} + 1)} \left(\frac{1}{1+\theta_i} \right)^{\lambda_{it}} \left(\frac{\theta_i}{1+\theta_i} \right)^{y_{it}} \qquad (13)$$

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:

$$\begin{aligned} E(y_{it}) &= \theta_i \lambda_{it} \\ V(y_{it}) &= (1+\theta_i)\theta_i \lambda_{it} \end{aligned} \qquad (14)$$

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

$$\frac{\Gamma(\sum_t y_{it} + 1)\Gamma(\sum_t \lambda_{it})}{\Gamma(\sum_t y_{it} + \sum_t \lambda_{it})} \prod_t \frac{\Gamma(\lambda_{it} + y_{it})}{\Gamma(\lambda_{it})\Gamma(y_{it} + 1)} \qquad (15)$$

which is free of the θ_i parameters. The likelihood of the entire sample is then obtained multiplying all the individual terms like in (13) and can be maximised with respect to β the parameters using conventional numerical methods.

2.4 The measure of the Absorptive Capacity

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.
Also in this case, we consider the interaction term between self citations and the spillover pool in the econometric model.

2.5 GMM Estimators

In panel data models, First-Differenced Generalised Method of Moments (GMM)[7] 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

$$y_{it} = \alpha y_{it-1} + \eta_i + \upsilon_{it} \qquad |\alpha| < 1 \quad (16)$$

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

$$E(\eta_i) = 0, E(\upsilon_{it}) = 0, E(\eta_i \upsilon_{it}) = 0 \text{ for i = 1 to N and t = 2 to T.} \quad (17)$$

We assume that the transient errors are serially uncorrelated

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

$$E(\upsilon_{it}\upsilon_{is}) = 0 \quad \text{for i = 1 to N and s} \neq \text{i} \quad (18)$$

and that the initial conditions yi1 are predetermined

$$E(y_{i1}\upsilon_{it}) = 0 \quad \text{for i = 1 to N and t = 2 to T.} \quad (19)$$

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

$$E(Z_i^{'}\Delta\upsilon_i) = 0 \quad (20)$$

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

$$Z_i = \begin{bmatrix} y_{i1} & 0 & 0 & \ldots & 0 & \ldots & 0 \\ & y_{i1} & y_{i2} & \ldots & 0 & \ldots & 0 \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\ 0 & 0 & 0 & \ldots & y_{i1} & \ldots & y_{iT-2} \end{bmatrix} \quad (21)$$

and $\Delta\upsilon_i$ is the (T-2) vector $(\Delta\upsilon_{i3}, \Delta\upsilon_{i4}, \ldots, \Delta\upsilon_{iT})'$. 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$\rightarrow \infty$ 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 (16), 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 (16), 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

$$E(\eta_i \Delta y_{i2}) = 0 \quad \text{for i =1 to N (22)}$$

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

$$E(u_{it} \Delta y_{it-1}) = 0 \text{ for I = 1 to N and t = 3,4…T (23)}$$

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 (20) and (22). 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

$$Z_i^+ = \begin{bmatrix} Z_i & 0 & 0 & ... & 0 \\ 0 & \Delta y_{i2} & & & 0 \\ 0 & 0 & \Delta y_{i3} & ... & 0 \\ ... & ... & ... & ... & ... \\ 0 & 0 & 0 & ... & \Delta y_{iT-1} \end{bmatrix} \quad (24)$$

where *Zi* is given by (21). The complete set of second-order moment conditions available can be expressed as

$$E(Z_i^{+}{}' u_i^+) = 0 \quad (25)$$

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:

$$y_{it} = \beta x_{it} + \eta_i + \upsilon_{it} \qquad (26)$$

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

$$E(x_{it}\upsilon_{is}) = 0 \text{ for i =1 to N and s} \leq t \quad (27)$$

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

$$E(x_{it-s}\Delta\upsilon_{it}) = 0 \text{ for t = 3 to T and s} \geq 2 \quad (28)$$

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

$$E(\eta_i \Delta x_{it}) = 0 \text{ for i = 1 to N and t = 2 to T} \quad (29)$$

and the following moment conditions are available:

$$E(\Delta x_{it-1}u_{it}) = 0 \text{ for i =1 to N and t = 3 to T} \quad (30)$$

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.

3. 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[8]. 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)[9], 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 competition that has to be confronted. Thus, the empirical results suggest that both beneficial and competitive effects from foreign knowledge spillovers are important.

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

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[10]. 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 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 (1998) 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.

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

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)[11], 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

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

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.

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	-0.094 0.240	0.04** 0.08***
Grunfeld (2004)	105 firms in Norway 1989-1996	Fixed-effect model	-0.0801 -0.0564	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.

4. CONCLUSIONS

This paper has provided an assessment of the recent literature on the knowledge spillovers and the Absorptive Capacity of the firms.
First, we have described the main econometric techniques to construct knowledge spillover pool and then we have showed their empirical evidence.
To this end, we have considered two possible dimensions: technological or geographic.
If the concept of a technological space is very attractive, its measure is not direct and the choice of a distance metric can affect the nature of results. There is also the question of heterogeneity in the technological space. Moreover, given the positioning of firms into the technological space, we cannot know to what extent two firms benefit from spillovers given the possible existence of asymmetrical information flows. The timing of spillover effects should also be considered. Because of lags in the diffusion of knowledge, spillover effects are probably not immediate.
In order to avoid these problems, the last and most recent approach to measure knowledge spillovers uses patent citations data[12]. The references to earlier patent documents and scientific papers contained in patent documents can be used to infer spillovers arising from the knowledge described in the cited patent to the knowledge in the citing patent.

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[12] See Hall, Jaffe, Trajtenberg (2001) for an explanation in using the patent citations data.

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