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Lionel Nesta

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Lionel NESTA
OFCE-DRIC
lionel.nesta@ofce.sciences-po.fr

Observatoire Français des Conjonctures Économiques
69, Quai d'Orsay 75340 Paris Cedex 07
Tel : 01 44 18 54 00 Fax : 01 45 56 06 15
E-mail: ofce@ofce.sciences-po.fr Web: http://www.ofce.sciences-po.fr

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Abstract

This paper examines the relationship between the characteristics of firm knowledge in terms of capital, diversity and relatedness, and productivity. Panel data regression models suggest that unlike knowledge diversity, knowledge capital and knowledge relatedness explain a substantial share of the variance of firm productivity. Activities based on a related set of technological knowledge are more productive than those based on unrelated knowledge because the cost of co-ordinating productive activities decreases as the knowledge used in these activities is being integrated efficiently. The impact of knowledge relatedness on productivity in high-technology sectors is higher than in other sectors.

1 Introduction

This paper explores the contribution of firm knowledge base, defined as knowledge capital, diversity and relatedness, to productivity. A firm's knowledge base is considered related when its scientific and technological competencies are complementary. As Penrose (1959) pointed out, firm performance depends not only on the stock, or capital, of its competencies but also on how diverse competencies are combined. I test for the importance of these three characteristics - knowledge capital, diversity and relatedness - using financial and patent data from a sample of the 156 world's largest manufacturing firms between 1986 and 1996.

The next Section reviews the previous theoretical and empirical literature. In Sections 3 to 5, I present the model, measures and data used to measure firm knowledge. The results are discussed in Section 6, leading to the conclusion of Section 7.

*Observatoire Français des Conjonctures Economiques, Département de Recherche sur l'Innovation et la Concurrence, OFCE-DRIC, 250, rue Albert Einstein, Sophia Antipolis, 06560 Valbonne, France, email: $lionel.nesta@ofce.sciences-po.fr$

2 The Model

Similarly to Griliches (1979), I start by using an augmented Cobb-Douglas production function. Firm output is a function of firm traditional factor endowment of capital and labour and firm knowledge stock:

$$Q_{it} = A \cdot C_{it}^{\beta} L_{it}^{\alpha} K_{it}^{\delta} e^{u_{it}} \tag{1}$$

where subscripts i and t refer to the firm i and the current year t, Q is output measured by sales, A is a constant, C is the gross value of plant and equipment, L is the number of employees. Traditionally in Eq.(1), K is defined as the firm's stock of knowledge. Suppose instead that knowledge stock K builds upon heterogeneous pieces of scientific and technical knowledge. These encompass specific technical artefacts, human capital, scientific principles guiding research activities (such as in the biopharmaceutical industry), etc. Assume for simplicity that activity k calls mainly on the stock of knowledge e dedicated to activity k: e may be thought of as the level of scientific and technical expertise dedicated to the k^{th} activity. Importantly, activity k may also benefit from knowledge associated with other activities l ($l \neq k$) held within the firm, depending on their associated level of relatedness τ_{kl}. Now let D be the number of productive activities within a firm: D represents the scope, or diversity, of the firm's knowledge base. It follows that:

$$k_k = e_k + \sum_{l \neq k}^{D} e_l \cdot \tau_{lk} \tag{2}$$

Eq. 2 means that the total knowledge stock k available to activity k is knowledge stock e_k and all other knowledge stocks e_l ($l{\neq}k$), weighted by their associated relatedness τ_{kl}. Generalising Eq.(2) to all productive activities within the firm yields the aggregate knowledge base K:

$$K = \sum_{k}^{D} e_k + \sum_{k}^{D} \cdot \sum_{l \neq k}^{D} e_l \cdot \tau_{lk} \tag{3}$$

For simplicity, I hold τ_{kl} constant across activities k's and l's, so that $\tau_{kl} = R$. Since $\sum_k e_k$ is firm knowledge capital, Eq.(3) simplifies to:

$$K = E \cdot [1 + (D-1) \cdot R] \tag{4}$$

Eq. 4 states that firm knowledge is a function of its total knowledge capital or expertise E, the number D of productive activities implemented within the firm and relatedness R across activities. Note that as D becomes larger, $[1 + (D-1) \cdot I] \approx [1 + D \cdot I]$, so that for large firms a reasonable approximation of the firm's knowledge base is $K = E \cdot [1 + (D \cdot R)]$. The amendment of K as done traditionally leads to insert two supplementary properties of firm knowledge: knowledge diversity and knowledge relatedness. The existence and relevance of this property is due to the collective nature of knowledge: in order to produce aggregate outcomes, diverse knowledge must be combined in a non-random and non-obvious way and integrated into a coherent base. Suppose for instance that firm i is composed of a set of entirely unrelated activities, implying no spillovers across activities ($R = 0$), the knowledge base K is reduced to its mere knowledge stock E. Conversely if firm i is composed of a set of related activities ($R > 0$), knowledge base K increases with the numbers D of productive activities implemented inside the firm weighted by their average relatedness R. In what follows I assume that:

$$K = E \cdot D \cdot R \tag{5}$$

Substituting **??** into 1, noting $\theta_k = \delta \times \varpi_k$, where ϖ_k, is the weight attributed to each of the three properties of firm knowledge base, and $K = \{E, D, I\}$, yields:

$$\begin{aligned} Q_{it} &= A \cdot C_{it}^{\beta} \cdot L_{it}^{\alpha} \cdot [E^{\varpi_E} \cdot D^{\varpi_D} \cdot R^{\varpi_R}]_{it}^{\delta} \cdot e^{u_{it}} \\ &= A_{it} \cdot C_{it}^{\beta} \cdot L_{it}^{\alpha} \cdot \prod_k k_{it}^{\theta_K} \cdot e^{u_{it}} \end{aligned} \tag{6}$$

or in the log form:

$$q_{it} = a + \beta \cdot c_{it} + \alpha \cdot l_{it} + \sum_k (\theta_k \cdot k_{it}) + u_{it} \tag{7}$$

where $k = \{e,\ d,\ i\}$ and β, α θ_k are the parameters of interest. The error term $_u it$ is decomposed into η_i, λ_{it} and e_{it}, where $\eta_i \sim$ IID(0,σ_η^2)is a 1×1 scalar constant capturing persistent but unobserved individual heterogeneity across firms such as managerial capabilities, firm propensity to collaborate, the type of economic environment, etc., $\lambda_{it} \sim$ IID(0,σ_λ^2) is a 1×1 scalar constant representing the time fixed effect which would capture positive or negative trends common to all corporations and $e_{it} \sim$ IID(0,σ_e^2)is the individual disturbance. Eq.(7) can be estimated by least squares.

3 Measures of Firm Knowledge

Perhaps the starting point of any work on knowledge should simply state that unlike physical assets, it is impossible for all the components of intangible capital to be accurately described. Therefore the observer must compromise and find only indirect traces of knowledge. For example, the contributions by Griliches have repeatedly used past R&D investments as a proxy for knowledge capital. Patent data have also been used for similar purposes and I base the three measures of knowledge capital, diversity and relatedness on the use of patent statistics. There are several pitfalls in using patent statistics, ranging from persistent sectoral differences in firm patenting to the quite heterogeneous economic value of patents (Archibugi, 1982; Pavitt, 1988). However, these critics lose their relevance when one tries to use patents statistics as a proxy for competencies.

Importantly, patent statistics provide information on technology classes in which firms develop technological competencies. This information is essential in experimenting for the expected positive role of knowledge diversity and knowledge relatedness . First, I proxy knowledge capital using the so-called permanent inventory method, and measure it as the cumulated stock of past patent applications using a rate of knowledge obsolescence of 15 percents per annum: $E_{it} = p_{it} + (1 - \delta) \cdot E_{i,t-1}$, where p is the number of patent applied for by firm i in year t and δ represents the rate of knowledge obsolescence.

Second, I define knowledge diversity as the breadth of firm knowledge base. Let p_{kit} be the number of patents applied for by firm i at time t in technology class k. In order to compensate for abrupt changes in firm learning strategies and introduce some rigidities in firm set of technological competencies, P_kit sums patent applications over the past five years: $P_{kit} = \sum_{\tau=0}^{5} p_{ki,t-\tau}$. Now let $d_{kit} = 1$ if the firm has developed competencies in technology k, ($P_{kit} > 0$), 0 otherwise. Knowledge diversity D is simply the number of technology classes in which firm develop scientific competencies over the past five years $D = sum_k d_{kit}$.

It should be pointed out, however, that as the patent stock increases, the likelihood of developing competencies in auxiliary technologies increases correspondingly. Thus measures E and D, namely knowledge capital and knowledge diversity, are likely to be correlated, which may induce multicollinearity problems when estimating their associated elasticities. I correct for it by computing the difference between the observed diversity D and the expected diversity $\hat{D}$, conditional on patent stocks: $D'_{it} = D_{it} - E[D_{it} \mid E_{it}] = D_{it} - \hat{D}_{it}$. By its very construction, D'_{it} can be either negative or positive. A positive (negative) measure of knowledge diversity informs on the relatively high (low) degree of knowledge diversity, given the firm's knowledge capital.

Third, the measure of knowledge relatedness in two steps: in a first step, I quantify technological relatedness between any two technologies k and l ; in a second step, I enter into the firm and use relatedness measures τ_{kl} to compute the weighted average relatedness of all technologies held within the firm.

In the first step, I estimate the relatedness measures τ_{kl} between any two technologies k and l by comparing the observed frequency f_{kl} with which two technologies k and l are used together with the expected frequency $\hat{f}_{kl}$ of their co-use. The observed frequency f_{kl} of technological co-occurrences may be derived from patent documents, describing their technological content, or by counting the number of agents (firms, universities, etc.) developing competencies in two technologies simultaneously. The computation of the expected frequency $\hat{f}_{kl}$ may be grounded on several methods (parametric vs. non parametric) but in any case it must be based on the hypothesis that the two technologies are randomly used together. In this paper, I calculate the expected frequency on the assumption that the distribution of random technological co-occurrences is hypergeometric (See appendix 1). The outcome of the comparison between f_{kl} and $\hat{f}_{kl}$ produces the relatedness measures τ_{kl}. Typically, τ_{kl} is a real number that can be positive or negative and may be thought of as the strength of the technological relationship between technologies k and l, or relatedness.

In the second step, I compute the weighted average relatedness WAR_k of technology k with respect to all other technologies within the firm. Similarly to Teece et al. (1994), the weighted average relatedness WAR_k of technology k is defined as the degree to which technology k is related to all other technologies $l \neq k$ present within the firm, weighted by patent count P_{lit}:

$$WAR_{kit} = \frac{\sum_{l \neq k} \tau_{kl} \cdot P_{lit}}{\sum_{l \neq k} P_{lit}} \tag{8}$$

WAR_{kit} is a measure of the expected relatedness of technology k with respect to any given technologies randomly chosen within the firm. WAR_{kit} may be either positive or negative, the former (latter) indicating that technology k is closely (weakly) related to all other technologies within the firm. Consequently, knowledge relatedness is defined as the weighted average of the WAR_{kit} measures:

$$R_{it} = \sum_{l \neq k} WAR_{kit} \times f_{kit} \quad where \quad f_{kit} = \frac{P_{kit}}{\sum_k P_{kit}} \tag{9}$$

Eq. 9 estimates the average relatedness of any technology randomly chosen within the firm with respect to any other technology. Again, this measure can be either negative or positive, the latter indicating that the firm's technologies are globally well related, while a negative value shows a poor average relatedness amongst the technologies in which the firm has developed competencies.

Applied to technology classes, the relatedness measure implies a different interpretation than when applied to activities, as done in Teece, et al. (1994). For Teece, et al., the prominent reason for related diversification lies in the similarity of activities amongst the firm's various production lines. Diversification is related when common competencies are shared in a (bounded) variety of business lines. This differs from our own interpretation of relatedness as applied to technologies. Technological relatedness τ_{kl} assesses the statistical intensity of the joint use of two given technologies and thus indicates that the utilisation of technology k implies that of technology l in order to perform a specific set of activities. In other words, technologies are related when their combination leads to specific technological functions that are not reducible to their independent use. Hence a reasonable interpretation of technological relatedness is that it indicates primarily the complementarity of the services rendered by two technologies. In the remaining of the paper, I shall refer to relatedness as assessing the complementarity between two technologies[1].

4 Data

The dataset used in this study is a compilation of a patent data set crossed with a financial data set. Concerning the former, I used the US Patent and Trademark

[1]For a thorough discussion and empirical analysis on the various foundation for technological relatedness, see Breschi, et al. (2003)

Office (henceforth USPTO) patent dataset provided by the National Bureau of Economic Research (Hall, et al, 2000). This dataset comprises more than 3 millions US patents since 1963, but requires some additional manipulations to convert it into a workable tool. First, using the information on the company name and year of application[2], I selected the most abundantly patenting manufacturing firms using Fortune 500 (August 1998). Because many of the world's largest companies operate outside the manufacturing sectors, such as banking or insurance, the selection yielded a sample of 162 companies, meant to be the world's largest manufacturing corporations. Second, the lack of data on firm consolidation in the USPTO patent dataset was overcome using the Who owns whom 2000 Edition. The consolidation exercise proves extremely useful, inflating the number of patents held by the firms in the sample by more than 300,000[3].

Third, the USPTO dataset provides, for each patent, one U.S. Patent technology class. An appealing opportunity is to use citations across patents to link technologies with one another. But as emphasised by Jaffe et al. (1998), citations remain a rather noisy event, for they encompass various legal matters regarding the validation of the technological novelty. Instead, information on the technological content of patents was completed by collecting all international technology classes (IPC) assigned to each US patent document[4]. The six-digit technology classes prove too numerous and I choose to use them at the three-digit level, analogous to a technological space of 120 technologies[5]. Because more than one technology may be listed within one single patent document, it is then possible to calculate the frequency with which two technologies are listed together[6]. This new patent dataset further enhances the computation, at the firm level, of the variables measuring knowledge capital (E), knowledge diversity (D) and knowledge relatedness (R) between 1968 and 1999.

The other data set, the 1997 edition of Worldscope Global Researcher, provides the financial variables at need. Firm sales are used as a proxy for output (Q), gross value of property plant and equipment proxies firm capital (C), whereas the number of employees is used to proxy labour (L). Ideally, one would

[2]Because the USPTO only advertise granted patents, I have only information about successful patent applications.

[3]The number of patents held by the world's largest manufacturing firms reached 500,000 prior to consolidation, but increased to 800,000 after controlling for consolidation. This illustrates the need for such exercise as well as it indicates the difficulty of the task. I am very thankful to Parimal Patel for providing me with these data.

[4]This was completed using the IPC code as displayed on the Internet Web Site of the European Patent Office. I am indebted to Bart Verspagen and Paola Criscuolo for their assistance during the automated process.

[5]The aggregation of technology classes into larger categories is a necessary but delicate exercise, because it influences negatively the variance of knowledge diversity and relatedness across firms. Prior literature (e.g. Jaffe, 1986; Hall et al., 2000), suggests that a thirty-dimensional technological space may be an appropriate aggregation. But since this paper deal with the largest manufacturing firms, using such a level of aggregation is likely to reflect product more than knowledge diversification while decreasing too severely the variance of knowledge diversity and relatedness across firms.

[6]Altogether, 751,935 US patents have more than one technology class, which proves adequate to measure technological relatedness.

Table 1: Descriptive Statistics. Pooled Sample

Variable	Obs.	Avg.	Std.Dev.	Min	Max
Q	1,608	21,713.4	21,950.4	38.1	167,038.9
C	1,608	16,969.2	18,613.3	41.2	126,372.3
NC	1,608	8,070.4	9,629.9	26.6	72,567.3
RD	1,337	949.5	1,234.6	1.1	8,900.4
L	1,608	91,432.5	96,541.4	647	876,000
E	1,608	1,697.2	2,001.0	2.6	12,171.3
D	1,608	49.3	20.7	398	
D'	1,608	0.0	14.3	-50.5	43.9
R	1,608	12.5	79.2	-66.1	1,943.4

Q:	Sales
C:	Gross Value of Plant and Equipment
NC:	Net Value of Plant and Equipment
RD:	R&D expenditures
L:	Number of employees
E:	Knowledge Capital
D:	Knowledge Diversity
D':	Unexpected Knowledge
R:	Knowledge relatedness

like to measure value-added to measure output (Q) more accurately, and control for labour quantity and quality by having data on the number of hours worked and on wages and compensation. Unfortunately, companies do not disclose such information systematically and the resulting figures proved to scarce to be of any use. We do not have information on value-added by firms and information on the number of hours worked or on education is not systematically provided in the company SEC filings. Therefore, the variable on labour input can only be used in ratio yielding the following functional form and model **??** becomes:

$$\left(\frac{Q}{L}\right)_{it} = A \cdot \left(\frac{C}{L}\right)_{it}^{\beta} \cdot \prod_{k} k_{it}^{\theta_K} \cdot e^{u_{it}} \tag{10}$$

where $\varphi = \alpha + \beta - 1$. The parameter φ is used as an assessment for constant returns to scale. If the parameter φ is not significantly different from nullity, i.e. $\varphi = 0$, the world's largest manufacturing firms are enjoying constant returns scale in production. However if φ is significantly different from zero, the production of the representative firm in the sample departs from an equilibrium of constant returns to scale, leaving prospect for either downsizing ($\varphi < 0$) or expansion in the scale of productive activities ($\varphi > 0$). Taking logs yields:

$$(q - l)_{it} = a + \beta \cdot (c - l)_{it} + \varphi \cdot l_{it} + \sum_{k} (\theta_k \cdot k_{it}) + u_{it} \tag{11}$$

where $k = \{e, d, i\}$. The left hand side of Eq. 11 is the logarithm of labour productivity, and β, φ and θ_k are the parameters of interest and can be estimated by ordinary least squares.

Additional data on the net value of property plant and equipment (NC), R&D investments(R), main industry group (two-digit IPC) and secondary industry groups are also used to control for the age of capital by calculating the ratio of net over gross capital (NC/C) , R&D intensity(R/Q), industry specific effects and product diversification, respectively. Financial data originally expressed in national currency have been converted in US dollars using the exchange rates provided by the Organisation for Economic Co-operation and Development (OECD). All financial data were then deflated into 1996 US dollars using the Implicit Price Deflator provided by the U.S. Department of Commerce, Bureau of Economic Analysis.

Compiling data from both the patent and financial datasets produced an unbalanced panel dataset of 156 companies observed between 1986 and 1996, yielding 1,608 observations. Tables I and II display the descriptive statistics for the set of variables and provide general information on the various industry groups of the sample (Standard Industry Classification - SIC two digit). The sample is composed of firms from 11 industry groups. These are rather heterogeneous, as they differ significantly in terms of their aggregate productivity

Table 2: Sectoral Decomposition of the Main Variables. 1986-1996

Sectors	N	Q	L	(Q/L)	$\Delta(Q/L)$	(R/Q)	E	D	D'	R
Chemicals and allied products (Including drugs)	29	13.0	55.9	232.6	4.83	6.47	1,705.5	46.2	-3.2	32.2
Communications	7	23.3	185.0	126.4	6.33	4.02	1,282.0	38.0	-8.2	67.4
Electronic and other electric equipment	17	22.7	129.9	174.7	5.99	6.67	3,162.1	60.1	-0.1	0.6
Food and kindred	6	21.7	135.1	160.8	6.12	1.42	359.9	29.2	-10.1	19.1
Instruments and related products	7	12.1	75.6	160.4	2.63	6.38	2,672.7	64.2	7.6	-5.7
Industrial machinery and equipment	16	21.6	98.2	219.6	5.24	5.05	3,134.2	54.9	-5.1	-5.0
Primary metal industries	11	13.0	34.9	372.6	5.75	1.67	501.9	46.4	6.1	-2.8
Oil and Gas Extraction	5	41.4	50.2	824.7	5.79	2.60	1,776.2	44.4	-5.5	16.2
Others	22	14.7	61.1	241.7	4.24	2.90	513.5	40.5	0.0	6.0
Petroleum and coal products	9	29.9	63.4	471.1	4.16	1.17	1,686.2	58.6	9.4	-5.9
Transportation equipment	27	35.4	141.2	251.4	6.78	4.50	1,434.4	51.2	3.9	17.5
Mean (Total)	(156)	21.7	91.4	237.4	5.31	4.59	1,697.2	49.3	0.0	12.5
F-Stat		8.35***	36.08***	5.55***	0.60	58.48***	44.80***	29.53***	24.00***	8.22***
R-Square		0.050	0.184	0.034	0.004	0.303	0.219	0.156	0.125	0.049

N: Number of Firms
Q: Deflated Sales (In Billions of 1996 US Dollars)
L: Number of Employees (In thousands)
(Q/L): Deflated Sales (Thousand of 1996 US Dollars) per Employee
$\Delta(Q/L)$: Annual growth rate of labour productivity
(R/Q): R&D intensity
E: Knowledge Capital
D: Knowledge Diversity
D': Unexpected Knowledge Diversity
R: Knowledge Relatedness

Table 3: Correlation Matrix. 1986-1996. Pooled Sample. N = 1,608

	$(q-l)$	$(c-l)$	l	e	d	d'	r	(NC/C)
$(q-l)$	1.000	0.852	-0.551	-0.065	-0.049	-0.032	0.021	-0.079
$(c-l)$		1.000	-0.452	-0.017	0.027	0.037	0.016	-0.196
l			1.000	0.487	0.432	0.194	-0.042	0.009
e				1.000	0.806	0.282	-0.173	-0.195
d					1.000	0.701	-0.420	-0.337
d'						1.000	-0.372	-0.263
r							1.000	0.223
(NC/C)								1.000

$(q-l)$: Natural logarithm of deflated sales per employee
$(c-l)$: Natural logarithm of gross capital per employee
l: Natural logarithm of labour
e: Natural logarithm of knowledge capital
d: Natural logarithm of knowledge diversity
d': Natural logarithm of unexpected Knowledge diversity
r: Natural logarithm of knowledge relatedness
(NC/C): Age of Capital

levels, research intensity, and knowledge characteristics (Table II). The largest sectors in the sample are: Chemicals and Allied Products, including Drugs (SIC 28, 29 corporations); Transportation Equipment (SIC 37, 27 corporations) Electronic and Other Electric Equipment (SIC 36, 17 corporations); Industrial Machinery and Equipment (SIC 35, 16 corporations). These sectors are generally highly intensive in R&D activities (see table II), with more than 5 percent of their sales invested in research. Thus, our findings are likely to be biased towards more research-intensive sectors, which is in line with the selection procedure of selecting the most abundantly patenting firms in the set of the world's largest manufacturing corporations. Consistently with Eq. 11, all variables are entered in logs, and their correlation coefficients are displayed in Table III.

5 Results

5.1 Preliminary results

Several econometric specifications have been used to estimate Eq. 11 and Table IV reports the main results. In Column (1), the results of Ordinary Least Squares (OLS) on the pooled sample show that all explanatory variables have a significant effect on labour productivity. Not surprisingly, the effect of physical capital $(c-l)$ is quite large (0.690) and in line with previous findings that the omission of materials in the production function overestimates the effect of physical capital (Griliches and Mairesse, 1984). The estimate for labour l is significant and negative (-0.197), which implies that the world's largest manufacturing corporations cope with steep decreasing returns to scale. This is hardly surprising, for the size of the world's largest corporations offers little scope for productivity gains related to increases in their scale of operations. The effect of the newness of capital (NC/C) is significant (1.005), suggesting a positive contribution of embodied technical progress to firm productivity.

The effects related to firm knowledge base are all significant. Consistently with the works of Griliches, knowledge capital e contributes positively to firm productivity (0.035), although knowledge capital as measured here differs from measures of R&D stocks. The negative sign of knowledge diversity (- 0.101) is in line with, but not identical to, the so-called "diversification discount". As product diversification, diversified knowledge bases impact negatively on firm productivity owing to increased agency costs and sub-optimal choices in investments across divisions. knowledge relatedness is highly significant (0.894). This conforms to the initial intuition that knowledge relatedness is related to coordination costs: firms diversifying in related activities are more productive because the cost of co-ordinating a heterogeneous set of productive tasks is simply inferior to that combining unrelated activities.

In columns(2)-(7), I explore alternative specifications of Eq.(7) in order to test for the robustness of these preliminary findings. Column (2) introduces a firm specific effect hi by converting all variables as differences from group (firm) means. This wipes out the unobservable and persistent heterogeneity across firms, which may alter the consistency of the estimates. The specification (Least Square Dummy Variable - LSDV) produces fairly robust estimates for most explanatory variables: large corporation cope with decreasing returns to scale; the effect of knowledge capital and integration remain highly significant whereas the effect of knowledge diversity to productivity becomes largely insignificant.

Eq.(7) relies on the critical assumption that the error term eit is serially uncorrelated. One can relax this assumption by adopting a dynamic representation of Eq.(7). First in column (3)-(5), all variables are expressed as differences from their value at time t - 1 weighted by parameter r representing first order autocorrelation (AR1): $x_{it} - x_{i,t-1}$, where x is any of the dependent and independent variables. The autoregressive model of column (3) produces a high ρ, which is near unity ($\rho = 0.968$). In column (4) all variables are entered as deviations form firm means. As a results, the estimated r decreases to a more standard value of slightly above 0.5. In the first difference where ρ is set to unity, knowledge capital and relatedness keep their high significance levels. This observation is quite satisfactory, as the autoregressive models with firm fixed effects is a fairly conservative method, where a substantial share of the information available in the dataset is swept away before the actual estimation.

The inclusion of a lagged dependent variable makes the standard panel estimation techniques, i.e. Ordinary Least Squares (OLS), inconsistent because the lagged dependent variable induces a correlation between the explanatory variables and the error term. A standard procedure for dealing with variables that are correlated with the error term is to instrument them and apply the instrumental Generalised Method of Moment (GMM) estimator along the lines suggested by Arellano and Bond (1991). In the one-step estimator (Column 6),

Table 4: Knowledge and Productivity. Pooled Sample

	OLS (1)	LSDV (2)	LSDVAR1 (3)	FD (4)	GMM (5)
Capital per employee	0.690	0.503	0.564	0.558	0.589
	[0.037]***	[0.020]***	[0.044]***	[0.049]***	[0.030]***
Labour	-0.197	-0.345	-0.347	-0.379	-0.373
	[0.019]***	[0.018]***	[0.039]***	[0.051]***	[0.033]***
Know. Capital	0.035	0.206	0.153	0.104	0.119
	[[0.012]***	[0.014]***	[0.032]***	[0.031]***	[0.022]***
Know. Diversity	-0.101	-0.033	-0.023	0.025	0.040
	[[0.026]***	[0.024]	[0.041]	[0.045]	[0.021]*
Know. Relatedness	0.894	0.589	0.285	0.133	0.285
	[[0.282]***	[0.158]***	[0.120]**	[0.067]**	[0.135]**
Newness	1.005	0.208	0.144	0.160	-0.211
	[[0.124]***	[0.086]**	[0.128]	[0.147]	[0.093]**
Intercept	-0.410	4.346	0.033	0.012	0.002
	[2.480]	[1.236]***	[0.016]**	[0.021]	[0.003]
Observations	1,608	1,608	1,608	1,448	969
Adjusted R^2	0.780	0.78	0.813	0.788	
Number of firms	156	156	156	155	134
Rho (Wald)			.554	1.000	(16,941***)
Sargan					56.2*
Ar1					-2.199***
Ar2					-1.422*

Standard errors in brackets.
significant at 10%; ** significant at 5%; *** significant at 1%.
All models include the full set of year dummies. The OLS specification includes a full set of (SIC two-digit) industry dummies. In GMM1 and GMM2, the set of explanatory variables are instrumented using two lags and using the log of R&D intensity (R/Q) as a supplementary instrument.

all the knowledge variables lose their significance, although the sign of knowledge capital and relatedness remains consistent with previous estimates. In the two-step estimator (Column 7), these variables recover their significance. This implies that in dynamic, positive changes in the knowledge variables, notably knowledge capital and relatedness, lead to positive changes in firm productivity Altogether, the various specifications show that: (i) large corporations face steep decreasing returns to scale; (ii) the stock of knowledge is a prime determinant of firm productivity; (iii) knowledge relatedness plays a significant and positive role in firm productivity. This is consistent with the proposition that effective knowledge relatedness lowers coordination costs across the productive activities within firms; (iv) in dynamic, positive changes in the previously mentioned variables entails positive changes in firm productivity; (v) knowledge diversification remain insignificant, suggesting that the breadth of firm knowledge is not linked to firm productivity.

Sub-sections 6.2 to 6.4 address three issues that may potentially affect the results: the characteristics of the sample; alternative measurement of firm knowledge; alternative econometric specification overcoming simplification that $K = E \cdot D \cdot R$.

5.2 Sample Bias

I deal with the first issue by decomposing the sample in several ways (reported in Table V). The parameter estimates reveal their usual robustness, but interesting insights emerge from the results. In column (8), I control for the possible contamination of results introduced by outliers located in the top and bottom 5 percentiles of observations for the dependent variables. The results are consistent with Table IV, although the estimated parameters, while keeping their significance levels, are all closer to zero. In column (9), I control for the R&D intensity of firms and include only observations with the ratio (R/Q) above 5 percent. The knowledge variables are fairly stable, but the estimate of knowledge relatedness is higher than for the whole sample. This suggests that high-technology firms rely more heavily on knowledge relatedness than less R&D-intensive firms.

This is further illustrated in columns (9)-(11) where observations have been grouped according to the sectoral aggregate R&D intensity as displayed in Table II. High-technology sectors comprise 53 large corporations from Chemicals (29 firms), Electronics (17 firms) and Instruments (7 firms), with an aggregate (R/Q) ratio above 6 percent. Medium-technology sectors comprise 50 large corporations from Industrial Machinery (16 firms), Transportation Equipment (27 firms) and Communications (7 firms), with an aggregate (R/Q) ratio between 4 and 6 percent. The low-technology sectors gather 31 firms (Oil, 5 firms; Food, 6 firms; Primary Metal, 11 firms; Petroleum, 9 firms) but exclude the miscellaneous category entitled "Others".

The results show that capital productivity is fairly stable across sectors, but the values of the labour estimate l suggests that decreasing returns to scale are not as steep in high-technology sectors as for others. This in turn may be due to several factors. However, it is consistent with the idea that such sectors constantly bring about new products that may keep the scale of productive activities closer to equilibrium. The knowledge variables exhibit an interesting gradual pattern, where knowledge capital and relatedness are significantly higher in high-technology sectors, whereas in low-technology sectors, the source of superior productivity does not seem to rely on the characteristics of firm knowledge base. In fact, one should be careful in rejecting the role of knowledge in low-technology sectors: it may well be that these firms have all achieved a satisfactory level of knowledge capital and relatedness that is a pre-requisite for their productive operations. Since knowledge is supposedly more stable, the knowledge variables are no more a discriminating criterion for high productivity, but remain a criterion for firm survival. Failures to accumulate and integrate knowledge in a productive fashion may lead to firm exit.

Table 5: Knowledge and Productivity. Sample Decomposition. Within Regressions on Pooled Sample. Dependent Variable: Deflated Sales per Employee

	90% Sample (6)	High (7)	Medium (8)	Low (9)	AMR (10)
Capital per employee	0.339	0.474	0.493	0.464	0.580
	[0.023]***	[0.037]***	[0.034]***	[0.046]***	[0.036]***
Labour	-0.254	-0.122	-0.407	-0.471	-0.305
	[0.019]***	[0.032]***	[0.032]***	[0.042]***	[0.035]***
Know. Capital	0.160	0.208	0.253	0.068	0.223
	[0.013]***	[0.025]***	[0.024]***	[0.041]	[0.023]***
Know. Diversity	0.019	-0.002	-0.005	-0.043	-0.007
	[0.022]	[0.055]	[0.032]	[0.082]	[0.034]
Know. Relatedness	0.578	1.296	0.588	1.352	0.79
	[0.144]***	[0.438]***	[0.197]***	[1.304]	[0.199]***
Newness	0.143	0.599	0.272	-0.407	0.119
	[0.080]*	[0.152]***	[0.142]*	[0.214]*	[0.139]
Intercept	5.619	-3.619	4.811	1.7	1.293
	[1.125]***	[3.323]	[1.631]***	[10.182]	[1.523]
Observations	1,446	549	508	326	639
Adjusted R^2	0.621	0.691	0.855	0.815	0.836
Number of firms	152	53	50	31	61
F-Stat	158.6***	80.9***	191.1***	92.5***	207.7***

See previous table footnote.

In columns (13) - (17), I experiment several decompositions of the sample. First, I test for the presence of a time effect by grouping the observations into two sub-periods: before or in 1990 and strictly after 1990. The results suggest that all aspects of firm knowledge become increasingly important through time. In the late eighties, all the knowledge variables are insignificant (Column 13), whereas in the nineties, knowledge capital and knowledge relatedness become positive and significant (Column 14). This echoes positively the rise of the so-called knowledge-based economies in the nineties. Second, I investigate the effect of geography on the production function by grouping firms in three sets: America, including Canada (Column 15), Europe (Column 16) and Asia (Column 17). All groups have a peculiar production function. American firms conform mostly to the general results. Firm productivity in European corporations is mainly based on knowledge capital. Asian corporations exhibit an unlikely production function since both diverse and integrated knowledge bases impact negatively on firm productivity. These regional particularities reflect the sectoral endowment of the geographic decomposition.

5.3 Mismeasurement of Knowledge

The second issue is related to the very measurement of the knowledge variables, the choice of which may affect the significance and signs of the relationships with productivity. Table VI provides the results of alternative measures of firm knowledge, whereas for comparison the first column displays the results from the basic specifications (Column 2 of Table IV). In column (18), I follow Griliches and Clark (1984) and Griliches and Mairesse (1990) and use the ratio (R/Q) to proxy knowledge capital. The results are as expected, positive and significant, although the estimate for knowledge relatedness loses its significance, due to its co-linearity with R&D investments.

In columns (19) and (20), I introduce additional measures of knowledge diversity. In Column (19), I introduce directly (the log of) knowledge diversity D, without correcting for firm patent stock. In column (20), I introduce knowledge diversity computed as the dispersion of firm competencies across technological areas: $D''_{it} = \mu_{P,it} \div \sigma^2_{P,it}$. This measures increases as firm competencies are distributed evenly across technologies[7].

The results show a persistent non-significance of technological diversification with firm productivity, whereas the other estimates are consistent with previous results. I do not, however, rule out the significant role of technological diversity in firm activities. First, diversification has been depicted to be a major input for innovative activities, simply because new ideas are more likely to emerge from a stock of diversified knowledge (Henderson and Cockburn, 1996). Switching the dependent variable with innovative output would certainly depict the positive and significant contribution of knowledge diversity to firm innovation. Second, technological diversification is being increasingly viewed as being a major characteristics of modern productive activities: firms differ more on the basis of their product portfolio than they do in terms of their technological competencies, precisely because the share of scientific and technical knowledge in productive activities has increased substantially, keeping the number of productive activities constant (Patel and Pavitt, 1994; Gambardella and Torrisi, 2000). Finally firm must develop technical competencies other than those they directly exploit in their very productive activities, first to benefit from technical spillovers from competitors (Jaffe, 1986), second to cope with the technological development of their most direct partners (Brusoni, et al., 2001).

In columns (21)-(23), I develop several measures of knowledge relatedness . Echoing Section 4, there are two main choices one must make when measuring

[7] Thus, measure is the inverse of the coefficient of variation, so that when , . This measure is not based directly on the number of patents held by the firm aver the past 5 years. Ideally, one wants to base on firm distinctive technological skills. Define the revealed technological advantage (RTA) as: $RTA_{it} = (P_{it}/\sum_k P_{kit}) \div (\sum_i P_{kit}/\sum_{ki} P_{kit})$. The numerator is the share of patents in technology k in the total patent stock of firm i. Likewise, the denominator represents the share of patents in technology k in the total patent stock of all actors. Therefore for a given technology, if the share of patents of firm i exceeds that of all actors, RTA will be greater than unity and firm i will have a Revealed Technological Advantage in technology k. See also Fai (2003) for a detailed analysis of the world's largest corporation based on the RTA.

Table 6: Knowledge and Productivity. Alternatives Measures of Knowledge Capital, Diversity and Relatedness. Within Regressions on Pooled Sample. Dependent Variable: Deflated Sales per Employee

	(RD/Q) (11)	Dispersion (12)	WAR_{NP} (13)	WAR'_{P} (14)	WAR'_{NP} (15)
Capital per Employee	0.573	0.499	0.509	0.513	0.512
	[0.024]***	[0.020]***	[0.020]***	[0.020]***	[0.020]***
Labour	-0.157	-0.348	-0.339	-0.336	-0.336
	[0.018]***	[0.018]***	[0.018]***	[0.018]***	[0.018]***
Know. capital	0.111	0.206	0.204	0.191	0.195
	[0.014]***	[0.015]***	[0.014]***	[0.014]***	[0.014]***
Know. diversity	-0.040	-0.001	-0.037	-0.037	-0.039
	[0.027]	[0.028]	[0.024]	[0.024]	[0.024]
Know. Relatedness	0.130	0.604	0.992	0.038	-0.020
	[0.344]	[0.158]***	[0.277]***	[0.015]**	[0.019]
Newness	0.010	0.205	0.211	0.184	0.180
	[0.103]	[0.086]**	[0.086]**	[0.086]**	[0.086]**
Intercept	7.015	4.199	3.771	8.641	8.763
	[2.639]***	[1.233]***	[1.438]***	[0.375]***	[0.374]***
Observations	1,338	1,608	1,608	1,608	1,608
Adjusted R-squared	0.765	0.780	0.780	0.779	0.778
Number of firms	139	156	156	156	156
F-Stat	282.3***	366.2***	366.4***	364.4***	362.7***

See previous table footnote.

knowledge relatedness within firms: in the first step, the choice of a relatedness measure τ_{kl}; in the second step, the choice of how to measure knowledge relatedness within the firm, given technological relatedness. Concerning the former, Appendix 1 suggests that there is no authoritative metrics for quantifying relatedness between technologies. Instead of relying on a parametric setting that produces relatedness τ_{kl}^{P}, one can also develop a non-parametric measure of technological relatedness τ_{kl}^{NP}, based on information theory. Regarding the latter choice, one can start by representing firm knowledge as forming a graph $G = (K, R)$, where K is the set of vertices, i.e. firm technological competencies, and R is the set of edges, i.e. technological relatedness, that links technologies together. In fact, Eq.(8) assumes firm competencies to form a fully connected graph; in a corporation with k technological competencies, all $k \times (k-1) \div 2$ pairs of technologies are included in the computation of WAR. Quite likely however, not all technologies within the firm are related to all other ones: only subsets of technologies relates to other subsets of technologies. To account for this, I follow Teece et al. (1994) and Breschi et al. (2003) and include only the $(m-1)$ strongest links that are needed to create a connected graph that comprises all firm competencies. This captures the strongest associations across technical areas k and l and is equivalent to depicting the maximum spanning tree from graph $G = (K, R)$. I thus rewrite Eq.(8) as follows:

$$WAR'_{kit} = \frac{\sum_{l \neq k} \tau_{kl} \cdot P_{lit} \cdot \lambda_{kl}}{\sum_{l \neq k} P_{lit} \cdot \lambda_{kl}} \tag{12}$$

where $\lambda_{kl} = 1$ if the link between technological competencies k and technological competence l is part of the tree. Because WAR' only includes the strongest links within the firm, WAR' is likely to produce measures of firm knowledge relatedness that are biased upwards, whereas conversely the previous measure is biased downwards. The results show that the measure of knowledge relatedness is generally robust. In column (21), knowledge relatedness based on τ_{kl}^{NP} remains both highly significant and positive, while in column (22), knowledge relatedness based on WAR' is positive and significant at 5 percent level. In column (23) however, knowledge relatedness based on both τ_{kl}^{NP} and WAR' becomes non significant, raising the issue regarding the very measure of knowledge relatedness. Clearly, knowledge relatedness embodies a large firm-specific element that is not captured with the methodology developed in the paper, and that goes beyond the means of the metrics suggested here. In all instances, this measure is likely to embody quite some noise, which in turn should bias the parameter estimate of knowledge relatedness θ_R downwards with respect to its unknown true value $\hat{\theta_R}$. Thus globally, the positive and significant relation between knowledge relatedness and firm productivity is quite supportive for the theory that more integrated knowledge are associated with lower coordination costs, thereby increasing significantly firm productivity.

5.4 Mispecification

The last issue investigate the validity of the linear specification, relying on the simplification that $K \equiv E \cdot D \cdot R$ whereas the original model implies that $K = E + (1 + (D - 1) \cdot R)$. Consistently with the previous results, I consider the estimate of knowledge diversity θ_D as being a residual, so that $\theta_D = 1 - \theta_E - \theta_R$. Substituting (4) into (1) yields:

$$\left(\frac{Q}{L}\right)_{it} = A \cdot \left(\frac{C}{L}\right)_{it}^{\beta} \cdot \left(E_{it}^{\varpi_E} + [1 + (D_{it} - 1)^{1-\varpi_E-\varpi_R} \cdot R_{it}^{\varpi_R}]\right)^{\delta} \cdot e^{u_{it}} \tag{13}$$

where the parameters ϖ_E and ϖ_R represent the weights associated with respectively knowledge capital and knowledge relatedness , whereas δ represents the overall effect of firm knowledge base on firm productivity. In the log form, Eq.13 becomes:

$$(q - l)_{it} = a + \beta \cdot (c - l)_{it} + \varphi \cdot l_{it} + log(E_{it}^{\varpi_E}[1 + (D_{it} - 1)^{\varpi_D} \cdot R_{it}^{\varpi_R}]) + u_{it} \tag{14}$$

All variables are expressed as deviations from firm means, wiping out the unobservable heterogeneity across firms. Importantly, $\log(E + (1 + (D - 1) \cdot R))$

Table 7: Non Linear Least Squares with Year and Firm Fixed Effect. Dependent Variable: Deflated Sales per Employee

	WAR_P		$WAR_P^{'}$	
	(16)	(17)	(18)	(19)
Capital per employee	0.592	0.519	0.593	0.514
	[0.018]***	[0.036]***	[0.018]***	[0.036]***
Labour	-0.234	-0.044	-0.234	-0.057
	[0.016]***	[0.031]	[0.016]***	[0.031]*
Know. Base	1.935	4.990	1.966	15.615
	[0.490]***	[1.441]***	[0.475]***	[3.475]***
Know. Capital	0.549	0.184	0.539	0.066
	[0.122]***	[0.053]***	[0.115]***	[0.017]***
Know. Relatedness	0.233	0.746	0.251	0.910
	[0.175]	[0.078]***	[0.167]	[0.025]***
Newness	0.082	0.626	0.080	0.585
	[0.085]	[0.154]***	[0.085]	[0.152]***
Intercept	-2.513	-6.064	-2.550	-18.770
	[0.588]***	[1.733]***	[0.572]***	[4.161]***
Observations	1,608	549	1,608	549
Adjusted R-squared	0.777	0.687	0.777	0.693
Number of firms	157	53	157	53
F-Stat	350.8***	76.3***	350.8***	78.3***

See previous table footnote.

can be negative, implying that Eq.14 cannot be estimated. To deal with this issue, all knowledge variables are standardised in such a way that $E, D, R \in [2; 3]$.

Table VII reports the results for the whole sample and for the high-technology sectors. It also distinguishes between the two measures of knowledge relatedness based on the WAR and WAR' computations. Although the parameter estimates for knowledge relatedness are at the borderline of significance (Columns 25 and 28), the results remain globally consistent with the previous remarks. First, the elasticity of deflated sales with respect to physical capital, although overestimated, remains quite stable across the specifications. The parameter for returns to scale is consistently negative for the sample as a whole, whereas firms active in high technology sectors operate in constant returns to scale.

The estimates depicting the elasticity of output with respect to firm knowledge are globally satisfactory. In column (24), parameter d is largely significant and positive, suggesting that a 1 percent increase in the firm total knowledge implies a 0.62% percent in firm output per employee. The weights ϖ_E and ϖ_R imply that $\varpi_R = 0.456$ and $\varpi_E = 0.175$, which is slightly lower than the basic specification from column (2). The weights ϖ_E and ϖ_R estimated from the identical specification using WAR' (Column 27) are more in line with the primary role of knowledge stocks over knowledge relatedness . They also suggest that the effect of knowledge diversity on firm productivity may not be a simple residual (columns 25 and 28). Computing $\varpi_D = \varpi_E - \varpi_R$ shows that the role of knowledge diversity becomes quite large (0.223 in column 25 and 0.210 in column 28) for the whole sample of firms.

The comparison of columns (25) with (26) and (28) with (29) suggests that in high-technology sectors, the role of knowledge relatedness is essential in boosting firm productivity. This is further compatible with the last estimates relating to the newness of physical capital (NC/C). Its large and significant effect in high-technology sectors suggests that much of firm productivity gains go through investments embodying in high-technology equipment. The supposedly higher technological turbulence in sectors such as chemicals (including the highly turbulent pharmaceutical industry), instruments and electronics challenges large corporation in their ability to assimilate and exploit new technical knowledge by integrating it into their own production function. Globally, the non-linear specifications produce estimates that compare well with previous estimations. There is an issue regarding the role of knowledge relatedness but the associated parameter estimate remains at the borderline of significance. By and large, its value is consistent with previous estimations: knowledge capital and knowledge relatedness are active component of firm productivity, especially in high-technology sector.

6 Discussion

The literature investigating the econometric relationship between knowledge and productivity has produced convincing evidence of the positive contribution of knowledge capital to productivity (Griliches, 1979 and following papers). Supplementary studies have yielded similar results, observing a quasi-systematic econometric relationship between some sort of knowledge capital and the general productivity of the firm. However, these studies have failed to address the relation between some characteristics of firm knowledge in terms of diversity and relatedness with firm economic performance. The reasons for this is that knowledge is generally considered homogenous and that, as a consequence, firm knowledge capital equates with the sum of homogeneous pieces of knowledge.

Instead, I argue that knowledge is intrinsically heterogeneous in nature because it refers to various scientific disciplines and is embodied in diverse technical devices. Such scientific and technical knowledge may further yield a variety of services, the exploitation of which is far from given to firms. As argued by Penrose (1959), firms must devote additional efforts to combine their resources, comprising their knowledge capital, in a non-random and non-obvious way. The relatedness of heterogeneous scientific and technical resources gives rise to ad hoc, local arrangements, thus leading to a persistent heterogeneity amongst competing firms.

Teece, et al. (1994) argue that the non-random organisation of activities has its very roots in the firm's competencies. When entering into new business lines, firms move into activities with similar scientific and technical competencies and common complementary assets. Thus, diversification strategy is not a free game;

hazardous and aggressive diversification may threaten the overall coherence of the firm and even its viability. Diversification inherently calls for some sort of relatedness, to increase the coherence of the firm's activities and the underlying knowledge base (Breschi, et al., 2003).

The economic justification for diversifying in related activities is that diversification comes at costs, stemming from increases in agency costs, sub-optimal choices in investments across divisions, imperfect internal capital market, etc. (Rajan, et al., 2000; Lamont, et al., 2001; Graham, et al., 2002). An additional cost is that diversification is likely to momentarily decrease the level of knowledge relatedness at both the plant and conglomerate level, thereby disrupting existing co-ordinating mechanisms. In turn, firms must devote part of their focus towards integrating these new sets of activities, competencies and technological knowledge with pre-existing ones.

Knowledge relatedness is in fact tightly linked with technological and/or business diversification and firm performance. In one of the earliest examples Rumelt (1974) showed that diversification is more likely to be successful within related activities sharing similar business lines and production chains. Later, Scott (1993) showed that diversification in related markets is purposive and tightly linked to higher profit rates. Schoar (2002) shows that although increases in diversification lead to a net reduction in total factor productivity, diversified firms enjoy higher productivity levels than single segment firms. Firms seek to benefit from economies of scope by diversifying their activities in related businesses (Montgomery, 1982; Ramanujam and Varadarajan, 1989; Montgomery and Hariharan, 1991, Teece, et al., 1994). Importantly, related diversification has been shown to be positively associated with higher growth rate of profits (Palepu, 1985). Scott and Pascoe (1987) demonstrates that R&D diversification in large U.S. manufacturing firms is found to be exploiting complementarities across research programmes that consolidate around related categories of products.

A tentative interpretation is that related diversification not only builds upon similar competencies, when similar sequences of productive activities are shared amongst several business lines, but also stems from vertical diversification, where the productive activities across businesses integrate complementary activities and competencies. Arguably, the cost of co-ordinating a set of productive activities decreases as the knowledge used in these activities is being integrated efficiently. Thus activities based on a related set of technological knowledge should prove more productive than activities based on a heterogeneous and unrelated set of activities: integrated knowledge bases should be positively linked with firm productivity.

7 Conclusion

This paper has aimed to generalise intriguing insights on the importance of knowledge in firm performance. It has analysed the relationship between output, physical capital, employment and three characteristics of firm knowledge -

knowledge capital, diversity and relatedness - on a sample of 156 of the world's largest corporations. The major finding is that knowledge capital and relatedness is important sources of productivity at the firm level. In fact, knowledge capital cannot be enough in explaining the contribution of intangibles to firm productivity. The intrinsically heterogeneous nature of knowledge implies that the way scientific and technical knowledge is combined impacts on firm productivity. The econometric results show that more integrated, better-articulated knowledge bases reach higher levels of productivity. The theoretical justification lies at the heart of economic theory: the cost of co-ordinating coherent knowledge bases is simply lower than that of co-ordinating unrelated pieces of knowledge.

Several issues relate to the heterogeneous nature of the sample, across time, industries and regions. Although there are important differences, these apply to the knowledge base as a whole more than they question the economic relevance of knowledge relatedness. Globally, the role of knowledge relatedness becomes stronger in knowledge-intensive sectors such as chemicals, drugs, electronics and instruments. In other sectors, its contribution remains positive and significant but significantly lower, even after controlling for plausible mismeasurements in the knowledge variables and possible mispecifications in the econometric model.

There is also the possibility of improving the statistical methodology in several ways. First, one can extend the data collection process to include quality and quantity of physical equipment and labour, to use value-added instead of gross output (sales), etc. Alternatively, one can refine the methodology on patent data by using citations in order to test whether technological relatedness is sensitive to the methods used to link technologies to one another. Moreover, the panel nature of our data suggests to extend the work on simultaneity amongst the variables, notably on R&D expenditures as a explanatory variables for the knowledge variables. The analysis has uncovered interesting relationships and left a number of issues open for further research. This suggests addressing the issue of knowledge relatedness as the dependent variable and the quantitative and qualitative efforts necessary in achieving desirable levels of relatedness. These encompass firm investments in research to pursue a given technological strategy; the set of partners involved in firm productive activities; and not least the investments in managerial resources itself.

Finally, one should keep in mind that firms seek several goals at once, some contradicting others. Unquestionably in the short run firms need to generate revenues. In the long run, they must anticipate as accurately as possible the potential technological opportunities that may impact directly on their productive operations. In other words, firms must invest in several research avenues, few of which may prove highly profitable. This tension between profitability and survival has long been identified (March, 1991). I suspect that the characteristics of firm knowledge must reflect these diverging goals, and future work shall investigate more systematically the behaviour of the knowledge variables with respect to alternative measures of firm economic performance.

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Appendix

Technological relatedness has been investigated in several publications (Sherer, 1982, Jaffe, 1986, Breschi et al., 2003). Similarly to Teece et al. (1994), I rely the so-called survivor principle that less efficient pairs of technologies are called to disappear ultimately and assume that the frequency with which two technology classes are jointly assigned to the same patent documents may be thought of as the strength of their technological relationship, or relatedness.

The analytical framework is similar to Breschi, et al. (2003) and departs from the square symmetrical matrix obtained as follows. Let the technological universe consist of a total of N patent applications. Let $p_{nk} = 1$ if patent n is assigned to technology k, $k = 1, , K$, 0 otherwise. The total number of patents assigned to technology k is thus $f_k = \sum_n p_{nk}$. Now let $p_{nk} = 1$ if patent n is assigned to technology l, 0 otherwise. Again, the total number of patents assigned to technology l is $f_l = \sum_n p_{nl}$. Since two technologies may co-occur within the same patent document, then $f_k \cap f_l \neq \oslash$ and thus the number f_{kl} of observed joint occurrences of technologies k and l is $f_{kl} = \sum_n p_{nk}p_{nl}$. Applying the latter to all possible pairs, we then produce the square matrix $\Omega(n \times n)$ whose generic cell is the observed number of joint occurrences f_{kl}. This count of joint occurrences is used to construct our measure of relatedness, relating it to some measure of expected frequency $\hat{f_{kl}}$ under the hypothesis of random joint occurrence.

There is no authoritative measure of $\hat{f_{kl}}$, and I shall consider below a parametric and non-parametric setting. In a parametric setting, one can consider the number f_{kl} of patents assigned to both technologies k and l as a hypergeometric random variable. The probability of drawing f patents with both technologies k and l follows the hypergeometric density function (Population K, special members f_k, and sample sizef_l):

$$P(f_k = f) = \frac{\binom{f_k}{f}\binom{N-f_k}{f_l-f}}{\binom{N}{f_l}} \tag{15}$$

where f is the hypergeometric random variable. Its expected frequency is:

$$\hat{f_{kl}} = E(f_{kl} = f) = \frac{f_k \cdot f_l}{N} \tag{16}$$

If the actual number f_{kl} of co-occurrences observed between two technologies k and l greatly exceeds the expected frequency $\hat{f_{kl}}$ of random technological cooccurrence ($f_{kl} > \hat{f_{kl}}$), then the two technologies are highly related: there must be a strong, non-casual relationship between the two technology classes. Inversely, when $f_{kl} < \hat{f_{kl}}$, then technologies k and l are poorly related. Hence, a parametric-based measure of relatedness τ^P_{kl} is:

$$\tau_{kl}^{P} = f_{kl} > \hat{f_{kl}} \quad (17)$$

Eq.17 may further be designed to control for the variance of the population defined. Assuming a hypergeometric distribution, the variance and relatedness measures are:

$$\sigma_{kl}^{2} = \hat{f_{kl}} \cdot \left(\frac{N - f_k}{N}\right) \cdot \left(\frac{N - f_l}{N - 1}\right) \quad (18)$$

Thus:

$$\tau_{kl}^{P} = \frac{f_{kl} - \hat{f_{kl}}}{\sigma_{kl}} \quad (19)$$

Eq. 19 has three attractive features. First, relatedness τ_{kl}^{P} is a real number that can be either positive or negative, the sign being a straightforward and intuitive indication of the relatedness between any two pairs of technologies [8]. Second, relatedness τ_{kl}^{P} is similar to a t-student, so that if $\tau_{kl}^{P} \in]-1.96; +1.96[$, one can safely accept the null hypothesis H_0 of no relatedness between technologies k and l. Third, τ_{kl}^{P} is a symmetric measure of technological relatedness so that relatedness τ_{kl}^{P} between k and l is strictly equal to relatedness τ_{lk}^{P} between l and k [9]. This may go some way against the intuition that knowledge and technologies form a hierarchical tree (Popper, 1972) but it offers the advantage of simplicity when dealing with multi-technology organisations.

In a non-parametric setting, one makes no assumption about the form of the distribution of technological co-occurrences across patents applications. A straightforward way to measure relatedness is then to compare the observed probability of any patent to combine technologies k and l with the expected probability, under the assumption that the event "patent with technology k" is independent from the event "patent with technology l". Let s_{kl}, s_k and s_l denote the shares of number of patent applications with respectively both technologies k and l, technology k, technology l in the total number of patents applications N: $S_{kl} = \frac{f_{kl}}{N}$; $S_k = \frac{f_k}{N}$; $S_l = \frac{f_l}{N}$. By definition, $s_k \cdot s_l$ is the share of patents with technologies k and l under the assumption that both technologies are independent, so that $s_k \cdot s_l$ represents the expected share $\hat{s_k}l$ with random technological co-occurrences. Using information theory (Theil, 1967), one can then define the non-parametric technological relatedness τ_{kl}^{NP} as follows:

$$\tau_{kl}^{NP} = log(\frac{s_{kl}}{\hat{s_{kl}}}) \quad (20)$$

The interpretation of Eq. 20 is straightforward. If $s_{kl} \div \hat{s_{kl}} > 1$, then $\tau_{kl}^{NP} > 0$: technologies k and l are rather well related. If $s_{kl} \div \hat{s_{kl}} < 1$, then $\tau_{kl}^{NP} < 0$: the technologies k and l are rather poorly related. Again, relatedness

[8]Relatedness measure τ_{kl}^{P} has no lower or upper bounds: $\tau_{kl}^{P} \in]-\infty; +\infty[$

[9]This is the case if one assumes that $N = N - 1$, so that $\sigma_{kl}^{2} \approx \hat{f_{kl}} \cdot (\frac{N-f_k}{N}) \cdot (\frac{N-f_l}{N})$. Considering the number N of patent applied for each year, it is a reasonable approximation.

is a real number that can be either positive or negative and is symmetric, so that relatedness between k and l is strictly equal to relatedness between l and k.

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