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Knowledge and Productivity in the World's Largest Manufacturing Corporations

Lionel Nesta *

Abstract

This paper develops a model linking firm knowledge with productivity. The model captures three characteristics of firm knowledge (capital, diversity and relatedness) that are tested on a sample of 156 of the world's largest corporations. Panel data regression models suggest that unlike knowledge diversity, knowledge capital and knowledge relatedness explain a substantial share of the variance of firm productivity. Relatedness matters because it lowers coordination costs between heterogeneous activities. Consequently, the traditional econometric specification has repeatedly underestimated by 15% the overall short-run contribution of intangible assets to firm productivity. This underestimation becomes fiercer in high technology sectors.

JEL classification: O3; L2; D24
Keywords: Knowledge; Productivity; Relatedness

1 Introduction

The literature investigating the econometric relationship between R&D and productivity has produced a large amount of evidence of the positive contribution of knowledge capital to firm productivity (Griliches 1986, Griliches and Mairesse 1983, Griliches and Clark 1984, Griliches and Mairesse 1984). Although convincing, these studies fail to address the issue of how firms cope with heterogeneous scientific and technical knowledge, the combination of which is likely to affect overall firm performance. The reasons for this is that knowledge is considered homogenous and that, as a consequence, firm knowledge capital equates with the sum of homogeneous pieces of knowledge.

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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 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 combination of these heterogeneous scientific and technical resources gives rise to *ad hoc*, local arrangements, 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. The reason for this is that diversification comes at costs, stemming from increases in agency costs, sub-optimal choices in investments across divisions and imperfect internal capital market (Rajan et al. 2000, Lamont and Polk 2001, Graham et al. 2002). An additional cost is that diversification is likely to decrease momentarily the technological coherence at both the plant and conglomerate level, thereby disrupting existing coordinating mechanisms. Firms must then devote part of their focus towards integrating these new sets of activities, competencies and technological knowledge with pre-existing ones. Therefore, diversification inherently calls for some sort of integration to increase the relatedness of the firm's activities and the underlying knowledge base (Breschi et al. 2003).

In fact, relatedness across productive activities has been shown to be tightly linked with 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, related diversification has been shown to be positively associated with higher profit rates (Scott 1993) and higher growth rate of profits (Palepu 1985). 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. The main justification for this lies in the presence of economies of scope, the benefit of which is likely to be a positive function of relatedness across business lines (Montgomery 1991, Ramanujam and Varadarajan 1989, Montgomery and Hariharan 1991, Teece et al. 1994).

It is well recognised that economies of scope arise when similar productive sequences are shared among several business lines. Still, related diversification also stems from vertical diversification, where the productive activities across businesses integrate complementary activities and competencies. Arguably, the cost of coordinating a set of productive activities decreases as the knowledge used in these activities is being combined efficiently. For example, Scott and Pascoe (1987) demonstrate that R&D diversification in large U.S. manufacturing firms is found to be purposive (to exploit complementarities across research programmes that consolidate around related categories of products). Thus activities based on a set of related technological knowledge should prove more productive than activities based on a heterogeneous and unrelated set of activities. In other words, integrated knowledge bases should be positively linked with firm productivity.

This paper develops a model that analyses the contribution of firm knowledge. This model generalises the traditional econometric specification where only intangible *capital* is assumed to play a significant role. Instead, the model captures three characteristics of firm knowledge (knowledge capital, diversity and relatedness), showing that the traditional model is the specific case for firms with completely unrelated scientific and technical knowledge. A firm's knowledge base is considered related when all scientific and technological competencies are found to be statistically inter-dependent. The paper tests 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 major finding is that unlike knowledge diversity, knowledge capital and relatedness are important sources of productivity at the firm level.

The paper is structured as follows. Section 2 develops the formal model. Sections 3 and 4 present the measures, data and econometric model used in this paper. The results are discussed in Section 5, leading to the conclusion of Section 6.

2 The Model

Similar 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:

$$Q_{it} = A \cdot C_{it}^{\beta} \cdot L_{it}^{\alpha} \cdot K_{it}^{\delta} \cdot \exp(u_{it}), \tag{1}$$

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, and L is the number of employees. Traditionally in Eq.(1), K is defined as the firm's stock of knowledge corrected for technical obsolescence: $K_{it} = \dot{k}_{it} + (1-\delta) \cdot K_{i,t-1}$, where $\dot{k}_{it}$ is new knowledge acquired by firm i at time t and δ represents the rate of knowledge obsolescence. There is no unique way of measuring $\dot{k}$, but R&D

expenses and patents, either granted or applied for, have been by far the most widely used proxies to date.

This approach has received a lot of attention, due both to its simplicity and to the significant improvement it has brought to our understanding of the contribution of intangible assets to productivity. However, the above formulation fails to address the issue of heterogeneous scientific and technical knowledge. These encompass specific technical artefact, human capital, scientific principles guiding research activities as in the biopharmaceutical industry and so on, the combination of which is far from being given to firms. Assume for simplicity that firms are composed of a vector $\mathbf{P}$ of D productive activities, $\mathbf{P} = [p_1, ..., p_d, ...p_D]$. Each activity p_d draws primarily on its associated scientific and technical expertise e_d, so that the firm's total expertise is vector $\mathbf{E} = [e_1, ..., e_d, ...e_D]$. However, activity p_d may also benefit from the expertise developed in other activities l ($l \neq d$), depending on the level of relatedness τ between technical expertise e_d and e_l. It follows that the knowledge base k used by the d^{th} activity is

$$k_d \equiv e_d + \sum_{l \neq d}^{D} e_l \cdot \tau_{ld}. \tag{2}$$

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

$$K \equiv \sum_{d}^{D} e_d + \sum_{d}^{D} \cdot \sum_{l \neq d}^{D} e_l \cdot \tau_{ld}. \tag{3}$$

For simplicity, let us hold τ_{ld} constant across activities d's and l's, so that

$\tau_{ld} = R$ across all productive activities within the firm. Since $\sum_d e_d$ is the firm's knowledge stock E, Eq.(3) simplifies to

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

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.

The amendment of K as done traditionally leads to insert two supplementary properties of firm knowledge: knowledge diversity and knowledge relatedness. The existence of these properties 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. Supposing for instance that firm i is composed of a set of activities with highly related knowledge ($R > 0$), knowledge base K increases with the number D of productive activities implemented inside the firm weighted by their average relatedness R. Conversely if firm i is composed of a set of activities with entirely unrelated technical knowledge, implying no spillovers across activities ($R = 0$), the knowledge base K is reduced to its knowledge stock E as measured traditionally. Thus this paper advances a more general formulation of firm intangible assets, where the traditional measure of K is the special and unlikely case where $R = 0$.

For the sake of simplicity, let us start by using the following approximation:

$$K \cong E \cdot D \cdot R. \tag{5}$$

Substituting (5) into (1), noting $\theta_K = \delta \times \varpi_K$, where ϖ_K is the weight attributed to each of the three properties $K = \{E, D, R\}$ of firm knowledge base yields:

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

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 $k = \{e, d, r\}$ and β, α and θ_k are the parameters of interest. Eq.(7) can be estimated using ordinary least squares. The error term u_{it} is decomposed into η_i, λ_t and ε_{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, and so on, $\lambda_t \sim$ IID(0,σ_λ^2) is a 1×1 scalar constant representing the time fixed effect that would capture positive or negative trends common to all corporations, and $\varepsilon_{it} \sim$ IID(0,σ_ε^2) is the individual disturbance.

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 components of intangible capital to be accurately described. Therefore the observer can only find indirect *traces* of knowledge. For example, the contributions by Griliches have repeatedly used (the accumulation of past) R&D investments as a proxy for knowledge capital. Patent data have also been used for similar purposes, and in what follows, 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 1992, Pavitt 1988). However, these critics lose their relevance when one uses patents statistics as a proxy for competencies, not as a proxy for innovative performance.

The other difficulty with the three knowledge variables is that one should expect them to be collinear, since empirical evidence suggests that firms diversify into related technologies (Teece et al. 1994, Breschi et al. 2003, Fai 2003). In this case, the decision to diversify is likely to be conditioned by issues regarding other knowledge variables. Typically, the decision to diversify will raise issues on the investments necessary to acquire any new technology, and on its complementarity with existing ones. As a consequence, processes of diversification will always increase knowledge stock E, but may or may not increase relatedness R, depending on the degree of complementarity between the newly acquired technology and those previously mastered by the firm. The question of the drivers of knowledge expertise, diversification and relatedness and of their interdependencies are important questions in their own rights, but they are beyond the scope of the present paper. Below, I deal with issues of multicollinearity from the statistical viewpoint only, to then consider all knowledge variables as independent predictors of the firm's productive efficiency.

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 grants using a rate of knowledge obsolescence of 15 percents per annum: $E_{it} = \dot{g}_{it} + (1-\delta) \cdot E_{i,t-1}$, where $\dot{g}_{it}$ is the number of patent grants of 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 $\dot{g}_{kit}$ be the number of patents grants of 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 the technology portfolio of the firm, P_{kit} sums patent grants over the past five years: $P_{kit} = \sum_{\tau=0}^{4} \dot{g}_{ki,t-\tau}$. 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 the firm develops 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 this 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 firm knowledge capital.

Third, the measure of knowledge relatedness in two steps: in the first step, I quantify technological relatedness between any two technologies k and l; in the second step, I assume that technological relatedness is given to firms, so that firms first observe all τ's and then choose their technology portfolio. Thus I use 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 the two technologies are jointly used with the expected frequency $\hat{f}_{kl}$ of their co-use. The observed frequency f_{kl} with which two technologies are used simultaneously is derived from patent documents. 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 A available on the website of the Journal). The outcome of the comparison between f_{kl} and $\hat{f}_{kl}$ produces the relatedness measures τ_{kl}, as detailed in Appendix A, Eq.(A-5). 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}:

$$WAR_{kit} = \frac{\sum_{l \neq k} \tau_{kl} \cdot P_{lit}}{\sum_{l \neq k} P_{lit}}. \quad (8)$$

Measure WAR_{kit} expresses 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:

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

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 these authors, 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].

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

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 Office (henceforth USPTO) patent dataset provided by the National Bureau of Economic Research (Hall et al. 2001). This dataset comprises more than 3 million US patent grants 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 (Fortune 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 proved 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 only one U.S. patent technology class per patent grant, hampering the computation of technological relatedness. 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

[2]The USPTO advertise only patent grants, not patent applications. This should not be a problem for computing all knowledge variables since it acts as a quality filter on the firm's patent portfolio. Note that I use the year of application, not the year in which the firm was awarded the patent.

[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 an exercise as well as indicating the difficulty of the task. I am very thankful to Parimal Patel for providing the information.

every US patent documents[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.

[Table 1 about here.]

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

[4] This was completed using *all* IPC codes as displayed on the Internet Web Site of the European Patent Office. I am indebted to Bart Verspagen and Paola Criscuolo for their much appreciated help 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 (Jaffe 1986, Hall et al. 2001), 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, of three million patents, 751,935 US patents have more than one technology class, which proves adequate to measure technological relatedness.

the following functional form:

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

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, and leaves 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 $k = \{e, d, r\}$. 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.

[Table 2 about here.]

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 1 and 2 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 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); and 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. Consistent with Eq.(11), all variables are entered in logs, and their correlation coefficients are displayed in Table 3.

[Table 3 about here.]

5 Results

5.1 Preliminary results

Several econometric specifications have been used to estimate Eq.(11), and Table 4 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 large (0.690) and in line with previous findings that state 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 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 are all significant. Consistent with the works of Griliches, knowledge capital 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. By the latter, we mean that assimilating technologies unrelated to those already mastered by the firm increases initial investments. These sunk costs should presumably affect productivity negatively, at least in the short run.

Knowledge relatedness is positive (0.894) with high significance. 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 coordinating a heterogeneous set of related productive tasks is simply inferior to that combining unrelated activities. This is consistent with the proposition that effective knowledge combination lowers coordination costs across the productive activities within firms. This finding is particularly important because it also implies that the overall effect of firm knowledge is larger that the mere effect of knowledge capital. That is, the traditional econometric specification has repeatedly underestimated the overall contribution of intangible asset to firm performance.

Columns (2)-(5) explore alternative specifications of Eq.(11) in order to test the robustness of these preliminary findings. Column (2) controls for unobserved heterogeneity by converting all variables as differences from group (firm) means: $x'_{it} = x_{it} - \overline{x_i}$, where x is any of the dependent and independent variables. This wipes out the unobservable and persistent heterogeneity across firms that may alter the consistency of the estimates. The specification (Least Square Dummy Variable - LSDV) produces significant estimates for most explanatory variables: large corporation cope with decreasing returns to scale, and the effect of knowledge capital and relatedness remain highly significant whereas the effect of knowledge diversity to productivity becomes insignificant.

Eq.(11) relies on the critical assumption that the error term e_{it} is serially uncorrelated. One can relax this assumption by adopting a dynamic representation of Eq.(11), converting all level variables into growth rates (log differences). This specification is robust to spurious regressions where significant estimates may be driven by their positive correlation with time. First in column (3), all variables are expressed as differences from their value at time $t-1$ weighted by parameter ρ representing first order autocorrelation (AR1): $x'_{it} - \rho x'_{it-1}$. The estimated ρ has a standard value of slightly above 0.5. In the first difference model (FD, Column 4) where ρ is set to unity, knowledge capital and relatedness keep their high significance levels, although the latter becomes significant at the 5 % level. 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.

[Table 4 about here.]

The inclusion of a lagged dependent variable makes the standard panel estimation techniques, 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 using the Generalised Method of Moment (GMM) estimator along the lines suggested by Arellano and Bond (1991). The GMM one-step estimates (Column 5) produce significant estimates for all variables, with the exception of knowledge diversity. They imply that from a dynamic perspective, positive changes in knowledge capital and relatedness lead to positive changes in firm productive efficiency. We also note that the significance of newness is low. Globally, these results are consistent with the idea that both knowledge capital and knowledge relatedness are significant drivers of productivity at the firm level.

One crucial question relates to the magnitude of the parameter estimates for both knowledge capital and knowledge relatedness. Fundamentally, these results suggest that knowledge relatedness is economically valuable, the extent to which remains difficult to assess. Given that little is known about investments by firms to improve knowledge relatedness, these results inform us exclusively on the significance and direction of the relationship between the firm's productive efficiency and knowledge relatedness. To gain insights on its relative weight, one way to go forward is to compute the standardised coefficients of variables using the Least Square Dummy Variable (LSDV) specification. The exercise shows that the standardised coefficients for knowledge capital θ_e^{sd} and knowledge relatedness θ_r^{sd} reach respectively 0.245 and 0.045. Hence the contribution of intangible assets is due primarily to its knowledge *stock*. However knowledge relatedness is of importance. Computing the ratio $\frac{\theta_r^{sd}}{\theta_e^{sd}+\theta_r^{sd}}$, I find that 16% of the short-run contribution of intangible assets to productive efficiency has been ignored by the usual specification that implicitly assumes $R = 0$. The coherence of the firm's technological diversification does have an impact on productive efficiency, and ignoring its contribution leads to a substantial underestimation of the overall contribution of intangible assets to firm performance.

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 role, contributing positively to firm productivity; (iv) positive changes in the previously mentioned variables entail positive changes in firm productivity; and (v) knowledge diversification remains insignificant, suggesting that the breadth of firm knowledge is not linked to productivity. The rationale for the important role of knowledge relatedness to firm productive efficiency lies in the fact that the cost of coordinating coherent knowledge bases is simply lower than that of coordinating unrelated pieces of knowledge. Such economies arise when diversifying in related technologies increases the potential for scope economies and lowers the sunk costs of investing in and mastering additional technologies.

Sub-sections 5.2, 5.3 and 5.4 address three issues that may potentially affect the results: the characteristics of the sample, alternative measures for intangible assets, and alternative econometric specifications overcoming the simplifications that $K = E \cdot D \cdot R$.

5.2 Sample Decomposition

I deal with the first issue by decomposing the sample in several ways. The results are reported in Table 5. The parameter estimates reveal their usual robustness, but interesting insights emerge from the results. In column (6), I control for the possible contagion of results from outliers by excluding observations located in the top and bottom 5 percentiles of observations for the dependent variables. The results are consistent with Table 4, although the estimated parameters, while keeping their significance levels, are all closer to zero (note the drop in the R-square). This suggests that a good deal of information on the relationship between tangible and intangible assets and firm productivity is found in the tails of the distribution. Interestingly, computing $\frac{\theta_r^{sd}}{\theta_e^{sd}+\theta_r^{sd}}$ inflates the ratio to 19%, reinforcing the argument that knowledge relatedness must be accounted for when assessing the contribution of intangible assets to firm productivity.

In columns (7)-(9), I control for the R&D intensity of sectors, where observations have been grouped according to the sectoral aggregate R&D intensity as displayed in Table 2. 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 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, but among other things, 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. Looking at the standardised coefficients, we observe that the $\frac{\theta_r^{sd}}{\theta_e^{sd}+\theta_r^{sd}}$ ratio reaches 21%, implying that in high-technology sectors, the impact of diversifying in related technology on labour productivity becomes considerably fiercer.

In low-technology sectors, the source of superior productivity does not seem to rely on the characteristics of firm knowledge. In fact, one should be careful in rejecting the role of knowledge in low-technology sectors for two reasons. First, 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. Failure to accumulate and integrate knowledge in a productive fashion may lead to firm exit. Second, the method using patent statistics may be more suitable for high technology sectors, where frontier technologies are more likely to be embodied in patent documents than in low technology sectors. More generally, the two explanations provided meet when one mentions that in low technology sectors, productivity growth may be imported from other sectors (i.e embodied from technical change developed in other sectors). In high-technology sectors, productivity growth would be more the results of within sector technical change.

[Table 5 about here.]

Last in columns (10) and (11), I investigate the effect of geography on the production function by grouping firms in two sets: America, including Canada (Column 10) and Europe (Column 11). Both groups have a peculiar production function. American firms conform mostly to the general results. The determinants of firm productivity in European corporations are similar with the exception of knowledge relatedness, whose parameter estimate, though positive, becomes non-significant. How should we interpret this? One can think of two competing interpretations. First, the observed regional differences reflect actual differences in production function, notably concerning the use of scientific knowledge and the way heterogeneous knowledge is combined. Second, these parameter differences are the outcome of differences in regional sector endowment. This second explanation implies that in Europe, knowledge relatedness should be a significant contributor to firm productivity in high technology sectors as well. To arbitrate between these two explanations, we ran an additional within regression for the sample of European firms in high-technology sectors. The results [7] show that indeed in high technology sectors, both knowledge capital and knowledge relatedness are active component of the production function in Europe.

[7] The results are not reported here, but can be obtained upon request to the author.

5.3 Using Alternative Measures of Firm Knowledge

One may object that our results are driven by the way with which we measure firm knowledge. This choice is important because it may affect the significance and signs of the relationships with productivity. In order to test the robustness of the results, table 6 provides the parameter estimates using alternative measures of firm knowledge. In column (12), I follow Griliches and Clark (1984) and Griliches and Mairesse (1984) 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 column (13), 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 measure is the inverse of the coefficient of variation and increases as firm competencies are distributed evenly across technologies $(\lim_{\sigma^2_{P_{kit}} \to \infty} D''_{it} \to +\infty)$. Importantly, this measure is not based directly on the number of patents held by the firm over the past 5 years, but on its revealed technological advantage, defined 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 so-called Revealed Technological Advantage in technology k.[8] This measure has the advantage of re-scaling all patent grants to a measure accounting for heterogeneous firm propensities to patent by relying on a more accurate idea of the firm's distinctive skills.

[8] Conversely, a value below unity indicates an area of relative weakness. See also Fai (2003) for a detailed analysis of the world's largest corporation based on the RTA.

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 a major characteristic 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 1997, Gambardella and Torrisi 1998). Finally firms must develop technical competencies other than those they directly exploit in their very productive activities, first to benefit from technical spillovers from competitors (Jaffe), and second to cope with the technological development of their most direct partners (Brusoni et al. 2001).

Last, I develop several measures of knowledge relatedness. Echoing Section 3, there are two main choices one must make when measuring knowledge relatedness within firms: the choice of a relatedness measure τ_{kl} and the choice of how to measure knowledge relatedness within the firm, *given* technological relatedness. Concerning the former, Appendix A 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 relate 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 $\lambda_{kl} = 1$ is 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.

[Table 6 about here.]

The results in Table 6 show that the measure of knowledge relatedness is generally robust. In column (14), knowledge relatedness based on τ_{kl}^{NP} remains both highly significant and positive. Remarkably, the $\frac{\theta_r^{sd}}{\theta_e^{sd}+\theta_r^{sd}}$ ratio for column (14) (τ_{kl}^{NP})

remains virtually unchanged at 15%, implying that the choice of the relatedness measure has virtually no effect on the amount of information brought by the identity $K \cong E \cdot D \cdot R$. In column (15), knowledge relatedness based on WAR'_P is positive and significant at the 5% level, while the $\frac{\theta_r^{sd}}{\theta_e^{sd}+\theta_r^{sd}}$ ratio drops to 12%. In column (16), 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 a bit of 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 is associated with lower coordination costs, thereby increasing significantly firm productivity. Although the ratio $\frac{\theta_r^{sd}}{\theta_e^{sd}+\theta_r^{sd}}$ drops to 12%, its level remains sufficiently large to motivate further research in this area.

5.4 The Non-Linear Specification

The last issue concerns 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 ω_D as being a residual, so that $\omega_D = 1 - \omega_E - \omega_R$. Substituting (4) into (6) yields

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

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

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

All variables are expressed as deviations from firm means, wiping out the unobservable heterogeneity across firms. Importantly, $\log(E + (1 + (D-1) \cdot R))$ 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 7 about here.]

Table 7 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 17 and 19), 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 columns (17) and (19), parameter δ is largely significant and positive, suggesting that firm total knowledge is tightly linked with firm output per employee. The weights ϖ_E and ϖ_R imply that knowledge capital is the prime intangible capital, more so than knowledge relatedness. They also suggest that the effect of knowledge diversity on firm productivity may not be a simple residual (columns 17 and 19). Computing $\varpi_D = \varpi_E - \varpi_R$ shows that the role of knowledge diversity becomes quite large (0.218 in column 17 and 0.210 in column 19) for the whole sample of firms.

The comparison of columns (17) with (18) and (19) with (20) 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 embodied 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 corporations 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. Its value is consistent with previous estimations: knowledge capital and knowledge relatedness are active components of firm productivity, especially in high-technology sector.

6 Conclusion

This paper has developed a model linking firm knowledge with productivity. This model generalises the traditional econometric specification where only intangible *capital* is assumed to play a significant role. Instead, our model captures three characteristics of firm knowledge (knowledge capital, diversity and relatedness) that are then tested on a sample of 156 of the world's largest corporations. The major finding is that unlike knowledge diversity, knowledge capital and relatedness are important sources of productivity at the firm level. The traditional econometric specification has repeatedly underestimated by about 15% the overall short-run contribution of intangible assets to firm performance. This underestimation becomes fiercer in high technology sectors.

Importantly, knowledge capital cannot exhaust 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, beyond and above the prime role of knowledge capital. The theoretical justification lies at the heart of economic theory: the cost of coordinating coherent knowledge bases is simply lower than that of coordinating 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.

The persistent non-significance of knowledge diversity contradicts the view that technological diversification is a major characteristic of modern productive activities: firms differ more on the basis of their product portfolio than they do in terms of their technological competencies. The reason for this is that for a given product line, the share of scientific and technical knowledge in productive activities has increased dramatically with the rise of the knowledge economy. However, firms must develop technical competencies other than those they directly exploit in their very productive activities in order to cope with technological turbulence. Thus, 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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Notes

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

[2]The USPTO advertise only patent grants, not patent applications. This should not be a problem for computing all knowledge variables, since it acts as a quality filter on the firm's patent portfolio. Note that I use the year of application, not the year in which the firm was awarded the patent.

[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 an exercise as well as it indicates the difficulty of the task. I am very thankful to Parimal Patel for providing the information.

[4]This was completed using *all* IPC codes as displayed on the Internet Web Site of the European Patent Office. I am indebted to Bart Verspagen and Paola Criscuolo for their much appreciated help 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 (Jaffe 1986, Hall et al. 2001), 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, of three million patents, 751,935 US patents have more than one technology class, which proves adequate to measure technological relatedness.

[7]The results are not reported here, but can be obtained upon request to the author.

[8] Conversely, a value below unity indicates an area of relative weakness. See also Fai (2003) for a detailed analysis of the world's largest corporation based on the RTA.

A Measures of Technological Relatedness

Technological relatedness has been investigated in several publications (Sherer 1982, Jaffe 1986, Breschi et al. 2003). Similar to Teece et al., I rely on 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. 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, $k = \{1, \ldots, K\}$, 0 otherwise. The total number of patents assigned to technology k is thus $f_k = \sum_n p_{nk}$. Now let $p_{nl} = 1$ 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 $\Omega(K \times K)$ 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 N, special members f_k, and sample size f_l):

$$P(f_{kl} = f) = \frac{\binom{f_k}{f}\binom{N-f_k}{f_l-f}}{\binom{N}{f_l}}, \tag{A-1}$$

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

$$\hat{f_{kl}} = E(f_{kl} = f) = \frac{f_k \cdot f_l}{N}. \tag{A-2}$$

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 co-occurrence ($f_{kl} > \hat{f_{kl}}$), 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 preliminary parametric-based measure of relatedness r_{kl}^P is

$$r_{kl}^P = f_{kl} - \hat{f_{kl}}. \tag{A-3}$$

Eq.(A-3) may further be designed to control for the variance of the sample at use. Assuming a hypergeometric distribution, the variance and relatedness measures are

$$\sigma_{kl}^2 = \hat{f_{kl}} \cdot \left(\frac{N - f_k}{N}\right) \cdot \left(\frac{N - f_l}{N - 1}\right). \tag{A-4}$$

Thus,

$$\tau_{kl}^P = \frac{f_{kl} - \hat{f_{kl}}}{\sigma_{kl}}. \tag{A-5}$$

Eq.(A-5) 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. Note that relatedness measure τ_{kl}^P has no lower or upper bounds: $\tau_{kl}^P \in]-\infty; +\infty[$. 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. 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 grants for each year, it is a reasonable approximation. 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 firms.

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 $\hat{s_{kl}}$ with random technological co-occurrences. Using information theory (Theil 1972), one can then define the non-parametric technological relatedness τ_{kl}^{NP} as follows:

$$\tau_{kl}^{NP} = log(\frac{s_{kl}}{\hat{s_{kl}}}). \tag{A-6}$$

The interpretation of Eq.(A-6) 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 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.

Table A-1 provides the descriptive statistics of the computed values for f_{kl}, τ_{kl}^{P} and τ_{kl}^{NP}, between 1968 and 2000. The total number of observed technological co-occurrences is above 138,000. It equates with a yearly mean number of 4,195 two-by-two technological combinations, whereas in a 120-dimensional technological space, the total number of potential co-occurrences is $K \times (K-1) \times \frac{1}{2} = 7140$. This gap suggests the presence of *some* determinism, possibly objective and scientific (Popper 1959), or sociological (Kuhn 1970), since the explored technological combinations are substantially less numerous than all their potential co-use. On average, the mean number of patents f_{kl} in which two technologies are used together is 44. Value f_{kl} ranges between 1 and 6,650, implying a considerable variance in technological co-occurrences. In fact, the distribution of f_{kl} is positively skewed, implying notable departure from normality.

Turning to the relatedness measures, the most immediate observation is that the mean value of both τ_{kl}^{P} and τ_{kl}^{NP} is negative and significantly below 0. This suggests that most technological combinations are unexpected as compared to what should be expected under the random co-occurrence hypothesis. This reflects, on the one side, behaviours of technological exploration, and on the other side choices of local (idiosyncratic) technological combination negatively captured by the metrics developed here. Both computations yield the same number of positive relatedness; 25% of relatedness measures are positive, derived from the same observations. In terms of distributional spread, the parametric approach produces a larger dispersion, with higher variance, lower minimal and higher maximal values. Last, the distribution of the non-parametric measure is closer to normality than the parametric counterpart, the latter having positive skewness and heavier tails. However in both cases, the Kolmogorov-Smirnov test of normality rejects the null hypothesis that the variables are distributed Normal.

Table A-1. Descriptive Statistics for f_{kl}, τ_{kl}^{P} and τ_{kl}^{NP}

	f_{kl}	τ_{kl}^{P}	τ_{kl}^{NP}
Number of Observations	138,464.00	138,464.00	138,464.00
Mean	43.83	-1.70[a]	-1.02[a]
Number of positive τ_{kl}	-	35,876.00	35,876.00
Standard deviation	162.46	10.04	1.57
Minimum	1.00	-62.50	-7.22
Maximum	6,050.00	155.40	4.52
Skewness	12.91	3.37	-0.05
Kurtosis	259.82	30.52	2.98
KS[b] Test: $H_0 : F(\Theta) \sim \aleph(\mu, \sigma^2)$	0.00	0.00	0.00

[a]Mean value significantly below 0 at 5% level
[b]KS: Kolmogorov-Smirnov test of normality

Which of these two measures should one choose? The most immediate advantage of the non-parametric approach lies in the interesting distributional properties of the computed τ_{kl}^{NP}. Its distribution is very close, albeit not equal, to normality. In this paper however, I opt for the parametric approach for two reasons. First, unlike the non parametric setting, the parametric approach has already received considerable attention in the literature. Hence this choice offers more consistency with previous works (Teece et al. 1994, Breschi et al. 2003, Nesta and Saviotti

2005). Second, the major advantage of τ_{kl}^{P} over τ_{kl}^{NP} is that it can be interpreted as a Student statistics, so that one can evaluate the statistical significance of the observed relationship between any two technologies. The rule of thumb here is that when $|\tau_{kl}^{P}| > 1.96$, one can reject the null hypothesis that the observed use of any two technologies equals their random co-use. In other words, technological relatedness is significant when $|\tau_{kl}^{P}| > 1.96$.

By way of conclusion, let us consider the strength of the relationship between both measures of technological relatedness. It appears that the Pearson's correlation coefficient and the Spearman's rank correlation coefficient between τ_{kl}^{P} and τ_{kl}^{NP} reach 0.70 and 0.86 respectively. This large correlation implies that our choice will affect the computations of R only marginally. In fact, Subsection 5.3 explores the robustness of the results by computing knowledge relatedness R at the firm level using the non-parametric measure τ_{kl}^{NP}. It confirms that this choice does not affect the direction and significance of the contribution of knowledge relatedness to the firm productive efficiency.

Table 1: Descriptive Statistics. Pooled Sample

Variable	Unit	Obs.	Avg.	Std.Dev.	Min	Max
Q	$10^9\times$ 1996 US$	1,608	21,713.4	21,950.4	38.1	167,038.9
C	$10^9\times$ 1996 US$	1,608	16,969.2	18,613.3	41.2	126,372.3
NC	$10^9\times$ 1996 US$	1,608	8,070.4	9,629.9	26.6	72,567.3
RD	$10^9\times$ 1996 US$	1,337	949.5	1,234.6	1.1	8,900.4
L	Head count	1,608	91,432.5	96,541.4	647	876,000
E	See Section 3	1,608	1,697.2	2,001.0	2.6	12,171.3
D	See Section 3	1,608	49.3	20.7	3	98
D'	See Section 3	1,608	0.0	14.3	-50.5	43.9
R	See Section 3	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 diversity
R: Knowledge relatedness

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
CHEM[a]	29	13.0	55.9	232.6	4.83	6.47	1,705.5	46.2	-3.2	32.2
COM[b]	7	23.3	185.0	126.4	6.33	4.02	1,282.0	38.0	-8.2	67.4
ELEC[c]	17	22.7	129.9	174.7	5.99	6.67	3,162.1	60.1	-0.1	0.6
FOOD[d]	6	21.7	135.1	160.8	6.12	1.42	359.9	29.2	-10.1	19.1
INST[e]	7	12.1	75.6	160.4	2.63	6.38	2,672.7	64.2	7.6	-5.7
IND. MACH[f]	16	21.6	98.2	219.6	5.24	5.05	3,134.2	54.9	-5.1	-5.0
METAL[g]	11	13.0	34.9	372.6	5.75	1.67	501.9	46.4	6.1	-2.8
OIL[h]	5	41.4	50.2	824.7	5.79	2.60	1,776.2	44.4	-5.5	16.2
OTHER[i]	22	14.7	61.1	241.7	4.24	2.90	513.5	40.5	0.0	6.0
PETROL[j]	9	29.9	63.4	471.1	4.16	1.17	1,686.2	58.6	9.4	-5.9
TRANSP[k]	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-Test[l]		31.98	36.08	5.55	0.29	58.48	44.80	29.53	22.92	8.22
R-Square[m]		0.167	0.184	0.034	0.002	0.303	0.219	0.156	0.126	0.049

[a] CHEM: Chemicals and allied products (Including drugs)
[b] COM: Communications
[c] ELEC: Electronic and other electric equipment
[d] FOOD: Food and kindred
[e] INST: Instruments and related products
[f] IND. MACH: Industrial machinery and equipment
[g] METAL:Primary metal industries
[h] OIL: Oil and gas extraction
[i] OTHER: Other industries
[j] PETROL: Petroleum and coal products
[k] TRANSP: Transportation equipment
[l] F-Test computed from the analysis of variance, where H_0 is all sector means are equal. All F-Test statistics significant at one percent level except for $\Delta(Q/L)$.
[m] R-Square represents the proportion of variance of all variables explained by the sector.
N: Number of firms
Q: Deflated sales (In Billions of 1996 US Dollars)
L: Number of employees (In thousands)
(Q/L): Deflated sales per employee (Thousand of 1996 US Dollars)
$\Delta(Q/L)$: 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

Table 4: Knowledge and Productivity. Pooled Sample

	OLS (1)	LSDV (2)	AR1 (3)	FD (4)	GMM (5)
Capital per employee	0.690	0.503	0.564	0.558	0.548
	[0.037]***	[0.020]***	[0.044]***	[0.049]***	[0.085]***
Labour	-0.197	-0.345	-0.347	-0.379	-0.325
	[0.019]***	[0.018]***	[0.039]***	[0.051]***	[0.070]***
Know. Capital	0.035	0.206	0.153	0.104	0.240
	[0.012]***	[0.014]***	[0.032]***	[0.031]***	[0.049]***
Know. Diversity	-0.101	-0.033	-0.023	0.025	-0.046
	[0.026]***	[0.024]	[0.041]	[0.045]	[0.058]
Know. Relatedness	0.894	0.589	0.285	0.133	1.017
	[0.282]***	[0.158]***	[0.120]**	[0.067]**	[0.334]***
Newness	1.005	0.208	0.144	0.160	0.515
	[0.124]***	[0.086]**	[0.128]	[0.147]	[0.287]*
Intercept	-0.410	4.346	0.033	0.012	-
	[2.480]	[1.236]***	[0.016]**	[0.021]	
Observations	1,608	1,608	1,608	1,448	1,448
Adjusted R^2	0.780	0.780	0.813	0.788	-
Number of firms	156	156	156	155	155
Hansen Test					146.4
Ar1					-1.56
Ar2					-1.02

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.
All GMM-difference results pertain to the first step. The Hansen tests correspond to the second step and are χ^2 distributed. All explanatory variables are instrumented using two lags.

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

	90% Sample (6)	High Tech. (7)	Medium Tech. (8)	Low Tech. (9)	AMR (10)	EU (11)
Capital per employee	0.339	0.474	0.493	0.464	0.580	0.285
	[0.023]***	[0.037]***	[0.034]***	[0.046]***	[0.036]***	[0.032]***
Labour	-0.254	-0.122	-0.407	-0.471	-0.305	-0.201
	[0.019]***	[0.032]***	[0.032]***	[0.042]***	[0.035]***	[0.025]***
Know. Capital	0.160	0.208	0.253	0.068	0.223	0.145
	[0.013]***	[0.025]***	[0.024]***	[0.041]	[0.023]***	[0.022]***
Know. Diversity	0.019	-0.002	-0.005	-0.043	-0.007	-0.034
	[0.022]	[0.055]	[0.032]	[0.082]	[0.034]	[0.058]
Know. Relatedness	0.578	1.296	0.588	1.352	0.790	0.150
	[0.144]***	[0.438]***	[0.197]***	[1.304]	[0.199]***	[0.247]
Newness	0.143	0.599	0.272	-0.407	0.119	-0.006
	[0.080]*	[0.152]***	[0.142]*	[0.214]*	[0.139]	[0.108]
Intercept	5.619	-3.619	4.811	1.7	1.293	9.317
	[1.125]***	[3.323]	[1.631]***	[10.182]	[1.523]	[1.903]***
Observations	1,446	549	508	326	639	512
Adjusted R^2	0.621	0.691	0.855	0.815	0.836	0.769
Number of firms	152	53	50	31	61	52
F-Stat	158.6***	80.9***	191.1***	92.5***	207.7***	110.4***

See previous table footnote.

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) (12)	Dispersion (13)	WAR_{NP} (14)	$WAR_P^{'}$ (15)	$WAR_{NP}^{'}$ (16)
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.

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

	WAR_P		$WAR_P^{'}$	
	(17)	(18)	(19)	(20)
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.

Knowledge and Productivity in the World's Largest Manufacturing Corporations

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Abstract

This paper develops a model linking firm knowledge with productivity. The model captures three characteristics of firm knowledge - capital, diversity and relatedness - that are tested on a sample of 156 of the world's largest corporations. 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 coordinating productive activities decreases as the knowledge used in these activities is being integrated efficiently. The traditional econometric specification has repeatedly underestimated by 15% the overall short-run contribution of intangible assets to firm productivity. This underestimation becomes fiercer in high technology sectors.