SEWPS

SPRU Electronic Working Paper Series

Paper No. 87

Intangible Assets and Market Value: Evidence from Biotechnology Firms

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June 2003

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Intangible Assets and Market Value: Evidence from Biotechnology Firms

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We examine the relationship between the characteristics of the firms' knowledge base in terms of knowledge capital and knowledge integration and the stock market value of 99 firms active in biotechnology during the nineties. Panel data regression models show that our measure of knowledge integration better explains the variance of a firm's market value than the more conventional variable of knowledge capital. This econometric relationship becomes stronger as the technology cycle reaches more mature phases. Meanwhile, profitable and research-intensive firms reach higher levels of market value.

Key words: Knowledge integration; intangible assets; market value; biotechnology; GMM.

JEL: G12, O31, L65.

This paper is based on research conducted at the Institut National de la Recherche Agronomique (INRA-SERD), University Pierre Mendès-France as part of Lionel Nesta's PhD research, which was supervised by Pier Paolo Saviotti.

I. Introduction

The valuation of firms by shareholders is a very important but not completely understood economic phenomenon. The empirical studies that have been carried out on the firm's market value point to three types of explanatory variables: current market opportunities, such as sales, profits, factor prices, etc.; tangible assets, measured by the value of firm's assets at replacement cost; and intangible assets – past and current R&D investments, patent portfolio and most recently the citations a firm has received for the patents it owns. In contrast to physical assets it is impossible for all the components of intangible capital to be accurately described. In this paper, we concentrate on intangible assets but we add to the scale of the research effort and to the patent stock of the firm a measure of the coherence of its knowledge base, defined as the way in which different components of the knowledge base of a firm are combined in a complementary manner.

In a previous study we found coherence of the knowledge base to be an important determinant of firms' innovative performance (Nesta and Saviotti, 2003). It follows that two firms with equivalent knowledge stocks may well have a different market value depending on their differential ability to combine the various pieces of knowledge that they have acquired by means of their R&D activities. This valuation need not result from a lengthy process of converting intangible resources into sales. It may be based on the current valuation of expected returns from the firm's research efforts and knowledge integration. In this paper, we will refer to this measure as either coherence of the knowledge base or knowledge integration, for coherence is itself the result of those integration activities that combine complementary knowledge in a non-random way. Knowledge integration is related to other economic issues such as the search for economies of scope, the division of innovative labour and the coordination of productive activities.

Little is known about the valuation by shareholders of knowledge integration, although previous work has repeatedly revealed some statistical relationships between *some* measures of related diversification and *some* measures of performance. We bring new evidence regarding the extent to which the coherence of the knowledge base is a discriminating determinant of the firms' market valuation. The use of knowledge integration as an explanatory variable in firms' market value is used together with more traditional variables, such as R&D expenditures, patent stocks and profit. These additional variables provide competing explanations that potentially may invalidate our intuition that more coherent firms are more valuable.

We study a sample of biotechnology firms, defined as active in biotechnology research and able to obtain future revenue from their subsequent innovation. Biotechnology firms belong to three main industries, namely the pharmaceutical, chemical and the agro-food industries, but are also seen as dedicated biotechnology firms (DBFs). DBFs were created to explicitly explore and develop new biotechnology products and services and thus are newer and smaller than traditional industries. Biotechnology is one of the technologies that emerged at the end of the 1970s and that have created enormous expectations of future economic development in several industrial sectors, the three mentioned above being the earliest to benefit. The period that we studied, the 1980s and most of the 1990s, covers the early emergence of a set of new technologies, including biotechnology, to the stock market bubble of the 1990s.

This paper is structured as follows. Section II presents alternative specifications for the valuation functions. In section III, the econometric specification used to estimate the parameters is presented. In section IV, we provide details of the dataset and of the metrics used to measure knowledge integration. Section V discusses the main results and section VI concludes.

II. *The Stock Market Valuation Function*

Questions relating to the market valuation of firms have gained momentum in the past two decades, providing growing evidence that intangible capital has become a very important determinant of firms' market value. This is consistent with the fact that, since the 1950s, intangible capital has overtaken physical capital (Abramowitz and David, 1996; Kendrick, 1994). In particular, this progression of intangible capital becomes understandable as we move towards the so-called knowledge based economy. Amongst the main components of intangible capital studied are R&D stocks, patent stocks and advertising (Griliches, 1981; Pakes, 1985; Jaffe, 1986; Cockburn and Griliches, 1988; Connolly and Hirschey, 1988; Hall, 1993; Hall, Jaffe, Trajtenberg, 2000). Other authors have pointed to the importance of focus in firm diversification (Wernerfelt and Montgomery, 1988; Scott and Pascoe, 1987), structure-performance relationship (Smirlock, Gilligan and Marshall, 1984) and degree of unionisation (Salinger, 1984). Each of these studies examines a subset of the potential components of intangible capital over relatively short periods of time. However, our understanding of the components and valuation of the firm’s intangible capital remains very partial and imperfect.

An ambitious attempt to understand the behaviour of the stock market over the period 1947-2000 was made by R.E. Hall (2001). He found that intangible capital is responsible for most of the variation in the market values of firms quoted in the Dow Jones index. However, the ratio of intangible to tangible capital swings very widely during the period studied and, at a given time (1988), the distribution of the same ratio amongst industrial sectors is extremely broad. Hall attempts to explain the inter-temporal swings of the stock market by means of the rational behaviour of economic agents valuing intangibles on the basis of the level and especially the growth of their cash flow. An entirely different hypothesis about the nature and fluctuations in the stock market value of firms is adopted by Perez (2003). In her view stock market crashes, such as those of 1929 or of 2000, are due to the decoupling of financial and industrial capital occurring *systematically* at particular stages of economic development. Perez espouses the long wave hypothesis (Freeman and Louça, 2001), according to which recurrent patterns of economic development can be seen at roughly 50 year intervals, starting with the emergence of new technologies and continuing through their subsequent diffusion and maturation.

The abovementioned contributions show that our understanding of the determinants of the firm’s market value comes down to three sets of questions: (i) What are the necessary components of a firm’s intangible capital and what are their roles as determinants of stock market value at a given time? (ii) How can we explain the distribution of the ratios of tangible and intangible capital amongst industrial sectors at a given time? (iii) How can we explain the inter-temporal variation of stock market values in the long run? In this paper, we will concentrate exclusively on the first question and rely on the following intuition: two firms with equivalent knowledge stocks might have a different market value depending on their differential ability to combine different pieces of knowledge coherently, that is, depending on their degree of knowledge integration.

The problem of the coherence of the firm was first raised in studies on firm diversification. 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. That a firm is not a collection of unrelated activities has been further demonstrated by the concept of *coherence* of the firm, as proposed by Teece, Rumelt, Dosi and Winter (1994). These authors 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 integration, to increase the coherence of the firm's activities and the underlying knowledge base.

We are concerned with the coherence of the knowledge base, but coherence can be manifested at other levels within firms. Firms may be coherent in terms of their product portfolio or of the markets in which they operate. Alternatively, firms may use coherent production activities, e.g. by sharing capital goods, or similar types of knowledge. It is possible that the achievement of coherence in one aspect may entail a reduction in the coherence of other aspects in the firm. One example is the concept of the life science company using a common knowledge base to produce products sold in highly heterogeneous markets (pharmaceuticals, agriculture, food, etc.) where the coherence of the knowledge base might have been obtained at the expense of coherence in outputs. The preferential achievement of coherence in a particular aspect of the firm can be considered an example of structural change within the firm. The particular aspect of a firm's activities in which coherence is differentially more important is likely to depend on the sector involved. In a highly knowledge intensive industry one would expect the coherence of the knowledge base to be a determinant of the general performance of the firm, including its stock market value.

We argue that knowledge integration is likely to be a particularly important aspect of a firm's activities in knowledge intensive sectors. We expect the market valuation of the firm to depend on a few particular aspects: knowledge integration, knowledge capital, R&D investment and profit. Like Griliches (1981), Salinger (1984) and Jaffe (1986), we start from a simple representation of the firm's market value V, where the latter is a linear function of sum of the current value of the firm's conventional assets C and the current value of its intangible resources IR:

$$V_{nt} = q_{nt} \cdot [C_{nt}, IR_{nt}] \tag{1}$$

Eq.(1) says that the market value of firm n, $n = 1,\ldots,N$, at time t, $t = 1,\ldots,T$, depends on the weighted sum of its conventional tangible assets C and intangible resources IR. The firm's tangible and intangible assets are valued at price q as follows:

$$q_{nt} = A \cdot P_{nt}^{b} \cdot R_{nt}^{l} \cdot exp(u_{nt}) \quad (2)$$

where A is a constant, P and R are respectively firm's profit and firm's research intensity. In Eq.(1) stock variables are entered while Eq.(2) introduces flow variables, which reflect current profitability and R&D investments. The term u is an individual and annual disturbance or error term, whose anatomy will be discussed later. While the representation, interpretation and measure of the firm's conventional assets are relatively straightforward, the representation of the firm's intangible resources demands more attention. Our baseline model follows previous contribution by viewing the firm's current value as:

$$V_{nt} = q_{nt} \cdot [C_{nt} + g \cdot K_{nt}] \quad (3a)$$

where K is a measure of the firm's knowledge stock, weighted by some rate of knowledge depreciation. No coefficient is associated with C. This is equivalent to assuming unity in the C coefficient, which in turn implies constant returns to scale in the valuation function. Alternatively, one could argue that in science intensive industries, a more integrated knowledge stock yields higher levels of innovation so that the value of the firm's intangible assets becomes:

$$V_{nt} = q_{nt} \cdot [C_{nt} + t \cdot I_{nt}] \quad (3b)$$

where I is a measure of knowledge integration. Eq.(3b) says that the stock market valuation of the firm depends exclusively on the way firms combine their technological portfolio. While we can find reasons to believe that knowledge integration is economically valuable, a perhaps more realistic representation of the firms' stock market value is:

$$V_{nt} = q_{nt} \cdot [C_{nt} + f \cdot K_{nt} \cdot I_{nt}] \quad (3c)$$

Eq.(3c) says that the stock market valuation of the firm depends on the interactions between the firm's knowledge stock and integration, what might be called its intangible resources. The previous models are very simplistic regarding the firm's stock market valuation function. The variables of knowledge capital and knowledge integration are exclusive of one another (3a and 3b) while the interactive model (3c) does not allow for independent estimations. A more sophisticated alternative is to model the firm's knowledge stock as follows:

$$V_{nt} = q_{nt} \cdot [C_{nt} + (g + t \cdot i_{nt}) \cdot K_{nt}] \quad (4a)$$

$$V_{nt} = q_{nt} \cdot [C_{nt} + (t + g \cdot k_{nt}) \cdot I_{nt}] \quad (4b)$$

$$V_{nt} = q_{nt} \cdot C_{nt} \cdot K_{nt}^{g} \cdot I_{nt}^{t} \quad (4c)$$

where i is (the log of) a quantitative measure of knowledge integration, k is (the log of) a measure of the firm's knowledge stock. Eq.(4a) says that the relative value of a unit of knowledge may vary a great deal depending on how knowledge is integrated within the firm. Eq.(4b) assumes implicitly that shareholders view the firm's intangible resources as a stock of knowledge, in which different pieces of knowledge play an important yet secondary role. Alternatively, we could assume that investors look primarily at the level of knowledge integration within firms. Eq.(4b) says that the value at which shareholders price knowledge integration also depends on the stock of intangible resources. Assume two firms achieve similar levels of knowledge integration, but one has a stock of knowledge that is twice as large as that of the other, it seems plausible that the intangible resources of the first firm should be valued at twice as much as the second firm. Lastly, we may model the firm's complete set of tangible and intangible assets in a more interactive way, where all variables *C*, *K* and *I* enter multiplicatively rather than additively. Eq.(4c) implies that a given degree of knowledge integration spreads over each unit of capital and of the knowledge stock. Alternatively, an additional unit of knowledge will also spread over all units of capital, given knowledge integration.

Substituting Eq.(2) into Eqs.(3a)-(4c), dividing through by C_{it}, taking logs, and using the approximation log (1 + x) ≈ x, yields respectively:

$$v_{nt} - c_{nt} = a + g \cdot K_{nt}/C_{nt} + b \cdot p_{nt} + l \cdot r_{nt} + u_{nt} \tag{5a}$$

$$v_{nt} - c_{nt} = a + t \cdot I_{nt}/C_{nt} + b \cdot p_{nt} + l \cdot r_{nt} + u_{nt} \tag{5b}$$

$$v_{nt} - c_{nt} = a + f \cdot (K \cdot I)_{nt}/C_{nt} + b \cdot p_{nt} + l \cdot r_{nt} + u_{nt} \tag{5c}$$

The same applies to models (4a)-(4c) yielding:

$$v_{nt} - c_{nt} = a + g \cdot K_{nt}/C_{nt} + t \cdot i_{nt} \cdot K_{nt}/C_{nt} + b \cdot p_{nt} + l \cdot r_{nt} + u_{nt} \tag{6a}$$

$$v_{nt} - c_{nt} = a + g \cdot k_{nt} \cdot I_{nt}/C_{nt} + t \cdot I_{nt}/C_{nt} + b \cdot p_{nt} + l \cdot r_{nt} + u_{nt} \tag{6b}$$

$$v_{nt} - c_{nt} = a + g \cdot k_{nt} + t \cdot i_{nt} \cdot + b \cdot p_{nt} + l \cdot r_{nt} + u_{nt} \tag{6c}$$

where the dependent variable (*v – c*) is equivalent to (the log of) Tobin's q (*V / C*), and the terms *g*, *t*, *b* and *l* are the parameters to be estimated. Note that the *b* and *l* parameters grasp the elasticity of the dependent variable with respect to the firm's current profit *p* and research intensity *r*. Through Eqs.(3a)-(4c), different models provide competing representations of the firm's intangible resources. In fact, we have no prior belief about the best model for the firm's market value, with the exception that: the degree of integration of the firm's heterogeneous stock of knowledge is economically valuable and, therefore, is reflected in its stock market valuation. Thus, the interest of a manifold formulation lies more in the search for a reliable representation of the firm's tangible and intangible assets. Depending on our estimations, we will be able to see: (1) what representation of the firm's total assets is best adopted by investors and thus whether our conclusions are model-specific or, on the contrary, hold for all models; (2) whether knowledge integration provides shareholders with economically valuable information.

III. Econometric Issues

Turning to estimation issues, we need to consider the panel nature of our dataset and the complex issues it introduces. Three problems need to be tackled in order to come up with reliable estimates of the parameters of interest: (1) cross sectional heterogeneity and heteroskedasticity; (2) serial correlation and the introduction of a lagged dependent variable as a possible regressor; (3) the possible endogeneity of the explanatory variables.

We develop a two-way error component model in which the error term u_{it} is decomposed into h_i, j_t and v_{it}, where $h_i \sim IID(0,s^2{}_h)$ is a 1×1 scalar constant capturing the individual heterogeneity across firms, $j_t \sim IID(0,s^2{}_j)$ is a 1×1 scalar constant representing the time fixed effect and $v_{it} \sim IID(0,s^2{}_v)$ is the individual disturbance:

$$u_{nt} = h_n + j_t + v_{nt} \tag{7}$$

In panel datasets where the number of firms is large, as is the case here, within group transformations may be preferred to the inclusion of a large matrix of dummy variables, which account for the firms' fixed effect. Ignoring for the moment the time specific effect j_t, the within group estimations may be performed by expressing all variables as deviations from the firm mean:

$$q_{nt} - q_{n\cdot} = \begin{Bmatrix} v \cdot (x'_{nt} - x'_{n\cdot}) + b \cdot (p_{nt} - p_{n\cdot}) + l \cdot (r_{nt} - r_{n\cdot}) \\ + (h_n - h_n) + (v_{nt} - v_{n\cdot}) \end{Bmatrix} \tag{8}$$

where $q = v - c$, x' is any of the knowledge resource variables in Eqs.(3a) to (4c) and ϖ represents the set of parameters g,t and f to be estimated. Eq.(8) can easily be extended to perform between regressions, as will be the case in this paper, where all variables are expressed as deviations from the group, i.e. the firm, means. The advantage of this is that it exploits differences across individuals that are by construction stable over time. While this specification properly controls for cross sectional heterogeneity, robust standard errors must correct for panel heteroskedasticity using the consistent variance-covariance matrix and applying White's correction.

The second issue of serial correlation is more tricky. Eq.(8) relies on the critical assumption that the error term is serially uncorrelated. We can relax this assumption by adopting a dynamic representation of the model of the following form:

$$\dot{q}_{nt} - r \cdot \dot{q}_{nt-1} = \begin{Bmatrix} v \cdot (\dot{x}'_{nt} - r \cdot \dot{x}'_{nt-1}) + b \cdot (\dot{p}_{nt} - r \cdot \dot{p}_{nt-1}) + l \cdot (\dot{r}_{nt} - r \cdot \dot{r}_{nt-1}) \\ + (\dot{v}_{nt} - r \cdot \dot{v}_{nt-1}) \end{Bmatrix} \tag{9}$$

$$\hat{r} = \frac{\sum_n^N \sum_{t=2}^T \hat{v}_{nt} \cdot \hat{v}_{nt-1}}{\sum_n^N \sum_{t=2}^T \hat{v}_{nt-1}^2} \quad with \quad \hat{v}_{nt} = \dot{q}_{nt} - \left[a + \hat{v} \cdot \dot{x}_{nt} + \hat{b} \cdot \dot{p}_{nt} + \hat{l} \cdot \dot{r}_{nt}\right] \tag{10}$$

where $\dot{x}$ represents the within transformation of the explanatory variables k, i, p and r. The parameter r represents the common factor representation for first order autocorrelation. Note that Eq.(9) forces the autoregressive estimator to be equal for all firms. Another model is to relax this assumption and to estimate autoregressive processes that are firm specific, what we call a firm-specific autoregressive model of order 1, or FSAR1. Eq.(9) is characteristic of a dynamic panel data model in which a lagged dependent variable is included in regressors. If $r = 0$, then Eq.(9) reduces to a simple static model in which the current market value of the firm is a function of its contemporaneous profit, research intensity and knowledge integration. If $r = 1$, the model is equivalent to the first difference model.

The inclusion of a lagged dependent variable makes the standard panel estimation techniques, i.e. Ordinary Least Squares (OLS), biased and inconsistent. The problem arises 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. Anderson and Hsiao (1981) suggest first-differencing Eq.(3a)–(4c) in order to eliminate the firm specific effects h_n:

$$q_{nt} - q_{nt-1} = \begin{Bmatrix} j \cdot (q_{nt-1} - q_{nt-2}) + v \cdot (x_{nt} - r \cdot x_{nt-1}) + b \cdot (p_{nt} - p_{nt-1}) \\ + l \cdot (r_{nt} - r_{nt-1}) + (h_n - h_n) + (v_{nt} - v_{nt-1}) \end{Bmatrix} \tag{11}$$

In the differenced form, the transformed error term becomes $(v_{nt} - v_{nt-1})$ and is by construction negatively correlated with the transformed lagged dependent variable $(q_{nt-1} - q_{nt-2})$. Anderson and Hsiao recommend instrumenting for $(q_{nt-1} - q_{nt-2})$ with either q_{nt-2} or $(q_{nt-2} - q_{nt-3})$, which are uncorrelated with the disturbance in (11) but correlated with $(q_{nt-1} - q_{nt-2})$. Relying on the findings of Arellano and Bond (1991) and Kiviet (1995), we prefer to use lagged differences as instruments. We define the following set of moment conditions:

$$\begin{cases} E\left[y_{nt-j}\left(v_{nt} - v_{nt-1}\right)\right] = 0 \\ E\left[x_{nt-j}\left(v_{nt} - v_{nt-1}\right)\right] = 0 \end{cases} \qquad \text{for } j = 2,\ t = 2, \ldots, T. \tag{12}$$

While the AH estimator is consistent as $N \to \infty$, its efficiency can be improved by using all possible lags of regressors as instruments. Arellano and Bond (1991) suggest using the matrix of instruments $Z = [Z'_1, \ldots, Z'_N]'$ where:

$$Z_n = \begin{bmatrix} q_{n1} & q_{n2} & 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & Dx_{n4} \\ 0 & 0 & q_{n1} & q_{n2} & q_{n3} & 0 & \cdots & 0 & 0 & 0 & Dx_{n5} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & \cdots & q_{n1} & q_{n2} & \cdots & q_{nT-2} & Dx_{nT} \end{bmatrix} \tag{13}$$

The instrument matrix Z can be expanded to take advantage of the additional independent explanatory variables. The instrument matrix that is optimal (i.e. efficient) differs according to whether the additional explanatory variables x are correlated with the fixed effects or not, and whether they will be treated as endogenous, predetermined or strictly exogenous. If x is to be treated as strictly exogenous, x is uncorrelated with past, current and future realisations of v. If x is to be treated as predetermined, x is uncorrelated with current and future values of v but is correlated with earlier shocks v. If x is to be assumed as endogenous, then it must be treated symmetrically with the dependent variable. Against little evidence of endogeneity and predeterminedness,[1] we assume that all explanatory variables are predetermined. The Generalised Method of Moment (GMM) estimator takes the form:

$$\hat{\imath}_{GMM} = (\mathbf{X'ZA_n Z'X})^{-1}\mathbf{X'ZA_n Z'Q} \tag{14}$$

where A_n is an appropriately chosen weight matrix. To estimate the optimal weight matrix of the GMM estimate, two different approaches can be used. Arellano and Bond propose one- and two-step estimators, respectively GMM1 and GMM2, that are computed as:

$$A_N = \left[\frac{1}{N}\sum_{n}^{N}\left(Z_n' H Z_n\right)\right]^{-1} \quad where \quad H_n = \frac{1}{2}\begin{bmatrix} 2 & -1 & \cdots & 0 & 0 \\ -1 & 2 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 2 & -1 \\ 0 & 0 & \cdots & -1 & 2 \end{bmatrix} \tag{15}$$

$$A_N = \left[\frac{1}{N}\sum_{n}^{N}\left(Z_n' ?v_n ?v_n' Z_n\right)\right]^{-1} \tag{16}$$

where v_n is the residual vector $Dv_n = (Dv_3,\ldots,Dv_T)$ obtained from a consistent first step estimation of the model. The above GMM specifications evidently rely on the absence of correlation between the instruments and the error term. The Sargan statistic (1958) is used to test the validity of the overidentified restrictions, under the H_0 hypothesis of no asymptotic correlation between the instruments and the perturbation. If the model is correctly specified, the statistic is chi-square distributed. Moreover, the GMM estimator is consistent if there is no second-order serial correlation in the error term of the first-differenced equation. Arellano and Bond propose to test the autocorrelation of the first and second of the residuals. They note that if the errors are uncorrelated, then the first differenced perturbations shall have negative first-order correlation but no second or higher order correlation. Thus, a test for the validity of the instruments (and the moment restrictions) is a test of second-order serial correlation in these residuals.

[1] A conventional though not satisfactory method (Maddala, 2002) of testing for endogeneity is to test for Granger causality. Appendix A tests for Granger causality between the dependent and the explanatory variables. We show that, under GMM estimations, the financial variables behave as endogenous to the system of equations: both profit p and the research effort r are affected and affect past, current and future realisations of the dependent variable q. The variables characterising the knowledge base, k and i, Granger cause the firm's market value but not *vice versa*. Thus, the so-called explanatory variables characterising the firm's knowledge base may well be affected by past and current values of performance (the firm's market value), but not by future ones.

IV. Data and Measurements

The variable called either coherence or knowledge integration constitutes the main new contribution of this paper to previous knowledge. Thus, we expose its underlying logic in greater detail than for the other variables.

The measure of knowledge integration is based on the degree of technological relatedness within the firm. Relatedness has been investigated in several publications (Sherer, 1982, Jaffe, 1986, amongst others). In this paper, we use the survivor measure of relatedness developed by Teece et al. (1994). Their measure is based on the idea that economic competition leads to the disappearance of relatively inefficient combinations of businesses. But, instead of applying it to industry SIC codes, we apply it to technologies (Breschi, Lissoni et al., 2003). Thus, we 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 departs from the square symmetrical matrix obtained as follows. Let the technological universe consist of K patent applications. Let $P_{ik} = 1$ if patent k is assigned to technology i, i = {1,…,n}, 0 otherwise. The total number of patents assigned to technology i is thus $O_i = \Sigma_k P_{ik}$. Now let $P_{jk} = 1$ if patent k is assigned to technology j, 0 otherwise. Again, the total number of patents assigned to technology j is $O_j = \Sigma_k P_{jk}$. Since two technologies may co-occur within the same patent document, then $O_i \cap O_j \neq \emptyset$ and thus the number J_{ij} of observed joint occurrences of technologies i and j is $\Sigma_k P_{ik} P_{jk}$. Applying the latter to all possible pairs, we then produce the square matrix Ω (n*n) whose generic cell is the observed number of joint occurrences J_{ij}.

$$W = \begin{bmatrix} J_{11} & \cdots & J_{i1} & \cdots & J_{n1} \\ \vdots & \ddots & & & \vdots \\ J_{1j} & & J_{ii} & & J_{nj} \\ \vdots & & & \ddots & \vdots \\ J_{1n} & \cdots & J_{in} & \cdots & J_{nn} \end{bmatrix} \tag{17}$$

This count of joint occurrences is used to construct our measure of relatedness, relating it to its expected value μ_{ij} under the hypothesis of random joint occurrence. Given this scheme, we consider the number x_{ij} of patents assigned to both technology i and j as a hypergeometric random variable of mean and variance (Population K, special members O_i, and sample size O_j):

$$m_{ij} = E(X_{ij} = x) = \frac{O_i O_j}{K} \tag{18}$$

$$s_{ij}^2 = m_{ij} \left(\frac{K - O_i}{K} \right) \left(\frac{K - O_j}{K - 1} \right) \tag{19}$$

If the actual number J_{ij} of co-occurrences observed between two technologies i and j greatly exceeds the expected value μ_{ij} of random technological co-occurrence, then the two technologies are highly related: there must be a strong, non-casual relationship between the two technology classes. Inversely, when $J_{ij} < \mu_{ij}$, then technology classes i and j are poorly related. Hence, the measure of relatedness is defined as:

$$t_{ij} = \frac{J_{ij} - m_{ij}}{s_{ij}} \qquad (20)$$

The relatedness square matrix Ω' with elements τ_{ij} has been computed for each year between 1981 and 1997. Calculations depart from all biotechnology patent applications assessed in the Derwent Biotechnology Abstracts (DBA). Today, more than 90 thousand patents are reported in the DBA, from 1965 to 1999, covering 40 intellectual property authorities. Over the period, the number of patent applications has increased almost every year. Because three years are needed for inventory purposes, and the curve drops precipitously after 1997, the analysis will be exclusively concerned with the period before 1997, and will thus be based on 80,163 patents. Each patent is described by its year of approval and by a vector of 30 technology classes, taking value 1 if a technology occurs in the patent, 0 if otherwise. For example, if technologies A and B occur within patent P, P can be described by the 30 dimensional vector $I = \{1,1,0\ldots0\}$.[2] The matrix Ω' is symmetrical, with 435 possible linkages between pairs of technologies. It is of importance that it displays the outcome of a large diversity of actors, differing in type (universities, research institutes or firms), country and size. Thus, the matrix Ω' provides us with some sort of *objectified biotechnological relatedness*, being the outcome of the interactions of a wide variety of actors.

Our measure of coherence is based on the degree of technological relatedness within the firm. Similar to what Teece et al. (1994) found, the weighted average relatedness WAR_i of technology i with respect to all other technologies within the firm is defined as: the degree to which technology i is related to all other technologies present within the firm, weighted by patent count p_j. It is thus a measure of the expected relatedness of technology i with respect to any given technologies randomly chosen within the firm. WAR_i may be either positive or negative, the former (latter) indicating that technology i is closely (weakly) related to all other technologies within the firm. For a firm developing competencies in a number - say five - technological DBA classes, five corresponding measures of WAR_i are computed. Consequently, the coherence of the firm's knowledge base is defined as the weighted average of the WAR_i measures:

$$I = \sum_{i=1}^{30} \left[WAR_i \times f_i \right] \quad \text{where } WAR_i = \frac{\sum_{i \neq j} t_{ij} p_j}{\sum_{i \neq j} p_j} \text{ and } f_i = \frac{p_i}{\sum_i p_i} \qquad (21)$$

Eq.(21) estimates the average relatedness of *any* technology randomly chosen within the firm with respect to *any* other technology. As in the previous cases, this measure can be either negative or positive, the latter indicating that the firm's technologies are globally

[2] Within one patent, a maximum of six technologies may be assigned, which leads to a maximum of 768,211 possible combinations in a thirty-dimensional technological space.

well related, while a negative value shows a poor average relatedness amongst the technologies in which the firm has developed competencies. Firms with a higher degree of knowledge relatedness are supposedly more integrated. We posit that the more integrated knowledge bases are also more coherent because they can better exploit the synergies, i.e. the complementarities, between the technologies.

In order to reduce the noise induced by changes in technological strategy, patent counts p_j are summed for the previous five years. This compensates for the fact that learning processes are time-consuming, due to certain rigidities in firms' technological competencies. Knowledge capital measures apply a similar correction by summing R&D expenditures over the same time span. Note that Eq.(21) involves two elements that might affect *I*. As already mentioned, relatedness is determined by the interactions of all actors for a given year, while patent count p_j clearly follows the firms' internal learning strategies. Therefore, a disconnection exists between the *yearly-objectified biotechnological relatedness* and the firm's knowledge base. Increases or decreases in technological relatedness might cause corresponding changes in the firm's coherence, even in the absence of any change in the firm's technological portfolio. This convincingly illustrates the fact that firms are embedded in a technological environment that they only marginally affect, while being substantially affected by it.[3]

The measure of coherence of the knowledge base developed is derived from the procedure used by Teece et al. (1994). While our procedure is formally similar to theirs, it differs in that it applies to the knowledge base rather than to outputs, and to the interpretation of the meaning of coherence. Teece et al. define coherence as relatedness. We think that both similar and complementary components of the knowledge base are related, but that we are more likely to find complementary than similar pieces of knowledge in a firm's knowledge base. We can expect a firm's competitive advantage in a knowledge intensive sector to rely on its ability to integrate *different* but *complementary* pieces of knowledge. This means not only choosing pieces of knowledge that are complementary in the sense of being jointly required to produce the firm's overall output, but also combining them effectively. The construction of a coherent knowledge base depends both on choosing the right pieces of knowledge and on integrating them effectively. Thus we use the terms coherence and knowledge integration interchangeably.

Besides knowledge integration, we measure knowledge capital *K* as the cumulated stock of past patent applications, using a 15 per cent depreciation rate. Obviously, patents are a noisy measure of knowledge capital for the distribution of the value of patented knowledge is highly skewed: few patents capture most of the returns from knowledge appropriation. A solution would be to use citation-weighted patent counts. Hall, Jaffe and Trajtenberg (2000) show that citation-weighted patent counts are more highly correlated with the firm's stock market value than mere patent counts. While we acknowledge the advantage of such a measure, the citation-weighted count is not applicable in our case. Most citation databases come from legal authorities such as the US, the World or the European patent offices. The Derwent database covers 40 patent authorities so that the gathering of citation-weighted patent counts would be almost impossible. Consequently, we use a simple patent count to

[3] Of course, the nature and causes of such changes in the technological environment involve a great range of phenomena. To discuss them at length goes well beyond the scope of this paper.

proxy the firm's knowledge capital, bearing in mind that this rudimentary metric is likely to bias downwards its potential impact on the firm's market value.

An alternative solution would be to rely on input variables such as R&D figures, since not all knowledge is patented or is patentable. Thus, focusing on the number of patents rules out additional knowledge that does not follow the path of appropriation. Conventional wisdom suggests that patent-based and R&D-based figures are alternative measures of the firm's knowledge capital. In this paper, we assume that each provides us with complementary information. Patent applications equate with past successes in R&D, while current research efforts supposedly predict future inventions. Thus we associate the former with the revealed knowledge capital while the latter informs us about the intensity of use of this knowledge capital. We will consistently use measures of R&D intensity, rather than mere R&D figures, to indicate the intensity of exploitation of the knowledge capital. Finally, data on the firms' research and development expenditures RD, operating income P, market capitalisation V and real assets C were collected from Worldscope Global Researcher (WGR), which provides financial information on public companies since 1989. All variables have been deflated in constant 1990 US dollars.

{TABLE I ABOUT HERE}

Descriptive statistics of the variables are presented in Table I. The empirical models (5a)-(6c) are estimated using a sample of 84 firms active in biotechnology. These firms were chosen on the basis of both patent activity and data availability. The sample is composed of 33 pharmaceutical firms, of which 17 are large chemical firms and 12 are active in agro-food industries. These industries have all benefited from biotechnology at different levels and for different purposes. However, for all these industries biotechnology has been a radical technological opportunity, the exploitation of which should be shown to be related to their innovative performance. Our sample also includes 22 firms categorised as DBFs, i.e. firms that were created on the basis of their distinctive competencies in biotechnology. In fact, the technological discontinuity induced by biotechnology created favourable conditions for the entry of these new actors into the competition (Kenney, 1986; Orsenigo, 1989; Grabowski and Vernon, 1994; Saviotti, 1998). Yet, the consequent rise in the number of DBFs has not led to the expected replacement of incumbents. For example, whilst large pharmaceutical firms invested heavily in building in-house research capabilities in biotechnology, DBFs found it very difficult to integrate complementary assets such as distribution channels, production facilities, etc. Consequently, successful integration for DBFs has been the exception rather than the rule. In our case, the DBFs chosen represent a particular sample of the entire DBF population. Because firms were chosen on the basis of availability of data between 1989 and 1997, all DBFs here are publicly held. Thus, they are generally the older DBFs - established before the mid-eighties, and as a result of integrative strategies, employing considerably more than 1,000 employees. The final database is an unbalanced panel indexed by firm and by year with 709 effective observations.

V. Results

We first ran four independent ordinary least square (OLS) regressions explaining (the log of) Tobin's q using alternatively six explanatory variables: knowledge capital over assets

(*K/C*), (the log of) knowledge capital (*k*), knowledge integration over assets (*I/C*), (the log of) knowledge integration (*i*), (the log of) profit (*p*) and (the log of) R&D intensity (*r*). The results are presented in table II.

Looking firstly at the R-square, the firm's profit is more highly correlated with the firm's market value than with R&D intensity, knowledge integration and knowledge capital. More generally, the financial-based variables of profit and R&D intensity have a higher explanatory power than the variables describing the characteristics of the firm's knowledge base in terms of capital and integration. This is consistent with the fact that patents are a noisy measure of innovation due to a great discrepancy in their economic value. Thus the use of patent stocks as a proxy for knowledge stocks brings measurement errors that are likely to attenuate the parameter estimate for knowledge capital.

The variables Profit and R&D intensity have a straightforward meaning in terms of elasticity of the dependent variable: a 1% increase in the firm's operating income, i.e. profit, raises the firm's valuation by .32%, while a 1% increase in the firm's research intensity yields a .22% rise. Using the fact that $q = log(V/C)$, $b =(¶V/V)/(¶P/P)$ and $l =(¶V/V)/(¶R/R)$, we derive the expected effect of a dollar increase in profit and research expenditures on the stock market valuation of firms. We find that a $1 rise in profit produces a $4.75 increase in the firm's market value, while a $1 rise in its research spending is valued at $6.10. These estimates are somewhat higher than those of Connolly and Hirschey (1988) and Griliches (1981) who found that an extra dollar of R&D expenditures adds $3.60 to the firm's excess value[4] and $2 to its market value. A similar level of inflation is found when analysing the value of an additional patent to the firm's knowledge stock (model 1 of table II). For the representative firm with mean assets and mean market capitalisation, our results suggest that an additional patent in the firm's knowledge stock is valued at $880,000. Previous estimations indicate that an additional patent is valued at approximately $200,000 (Connolly and Hirschey,1988; Griliches, 1981; Hall, Jaffe and Trajtenberg, 2000) and $810,000 (Pakes, 1985).

{TABLE II ABOUT HERE}

Why are our estimates biased upwards in comparison with earlier studies? A possible explanation could be the science-based character of biotechnology. Firms that invest less in R&D are likely to lose track of the latest developments in biotechnology, while more research intensive firms are better positioned to come up with successful innovations. Likewise, the expected aggregate revenue derived from royalties ought to reach higher levels in firms with a larger knowledge stock, though more uncertainty should also be associated with significantly higher expected returns from patent applications. Thus our estimate may well reveal the peculiar scientific and technical intensity of biotechnology as distinct from less technology-based sectors. Knowledge capital and R&D intensity do provide investors with key information on the current expected value of firms.

But is knowledge integration valuable? In table II, the parameter estimates of knowledge integration are both positive and significant, suggesting that more integrated knowledge

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[4] The excess value is defined as the market value of common assets plus book value of debts minus the book value of tangible assets.

bases are associated with higher market capitalisation. It is interesting, but, alas, difficult to compare the parameter estimates of knowledge integration with those of knowledge capital. Even in the case of model (4) where the parameter *t* does indeed represent elasticity, little meaning can be attached to it. Instead, we use the F-statistic that provides a measure of the explanatory power of the variables. We observe that in model (4) the explanatory power of the knowledge integration variable (F-statistic = 29.50) is twice as large as that of the more conventional variable of knowledge capital (model 2, F-statistic = 15.26). When normalised by the firm's stock of capital, the explanatory power of the knowledge capital variable K/C is twice as large as that of I/C (model 3). These preliminary and indicative results suggest that knowledge integration as measured in this paper is economically valuable, the extent to which this is so remains difficult to assess.[5]

Albeit satisfactory, the previous results draw on oversimplified specifications. As specified in Eqs.(5a) to (6c), all variables must enter the model simultaneously and, thus, the "horse-race" specification where all variables compete for the highest explanatory score (Hall, Jaffe and Trajtenberg, 2000) is likely to conceal additional insights. We investigate the relevance of the six empirical models (5a) to (6c) relating the firms' market value to its characteristics. Because the dependent variable is the same and the number of explanatory variables is the same, the R-squares are directly comparable for models (5a)-(5c) and models (6a)-(6c). Table III presents the results of Eqs.(5a)-(5c) for different econometric specifications reported in rows, respectively the OLS specification, Least Square Dummy Variable (LSDV) or fixed effect specification, the between (BTW-deviations from firm means) estimates, the first difference (FD) estimates ($r = 1$), the autoregressive models of order 1 ($0 < r < 1$), the AH two-stage estimators, and the GMM1 and GMM2. Their purpose was to test the robustness of the results, particularly regarding the introduction of a radically new explanatory variable of knowledge integration.

{TABLE III ABOUT HERE}

We find evidence that knowledge integration better explains the variance in the firms' stock market value than its knowledge capital counterpart, although statistically model (5b) is not significantly different from model (5a). We observe that the joint effect of knowledge capital and integration is positively and significantly linked to the firms' stock market value (model 5c). When controlling for firm specific effects (LSDV model), the least square estimator becomes positive as opposed to the OLS estimator, showing that after controlling for firm heterogeneity, there is a relationship between the characteristics of the knowledge base and the firm's market value. As expected, the FD specifications yield insignificant estimates for both the knowledge capital and knowledge integration variables, but are reassuringly of the same signs as those produced in other specifications. This suggests that the knowledge variables are not spuriously correlated with the dependent variables. The more traditional variables of R&D and profit perform equally well in most types of specification. Firms with higher profits, which devote a substantial share of their resources to research, reach higher stock market values.

[5] A possibility is to regress the dependent variable on the *ranked* values of knowledge integration. The results show that a one-point increase in the *ranked* value of knowledge integration is associated with a $m32.8 increase in the stock market valuation of the firm. Given that little is known about investments by firms to improve knowledge integration, this remains not very informative.

The estimates of the financial variables profit and R&D intensity remain robust both in terms of the model considered (5a) to (5c) and of the various estimators. Assuming that the estimated elasticities *ß* and l of the firm's stock market value with respect to profit p and R&D intensity r average respectively around .290 and .235,[6] we find that a $1 rise in the firm's profit produces a $4.30 increase in the firm's market value, while a $1 rise in its research spending is valued at $6.50. These figures compare well with those in table II, showing strong robustness of the parameter estimates. Focusing on the parameter estimates γ and t, similar conclusions cannot be drawn. Model (5a) witnesses a drop in the estimate of knowledge capital g stabilising at approximately .220,[7] implying that the average value of a biotechnology patent is $330,000. This estimate is somewhat closer to the estimates of Connolly and Hirschey (1988), Griliches (1981) and Hall, Jaffe and Trajtenberg (2000). Model (5b) also shows a drop in the estimate of knowledge integration t to approximately .280. Therefore, more complete models, where the knowledge variables are entered with supposedly more robust variables, do downwardly influence the value of the knowledge estimates. An intuitive and tentative explanation is that although the characteristics of the knowledge base explain a significant portion of the variance in firm's market value, the primary drivers for shareholders, unsurprisingly, continue to be financial, i.e. profitability and research-intensity.

This evidence supports the view that the diversification in the firm's knowledge base must exploit the complementarities between the various technologies mastered by firms. This corroborates the findings of Scott (1993) where the author notes that purposive diversification leads to productivity growth, and those of Nesta and Saviotti (2003), who empirically found that coherent diversification leads to higher levels of productivity in pharmaceutical research. As expected, the stock market valuation of firms does eventually reflect the productive value of their intangible assets and, more particularly, that coherent knowledge bases are considered by shareholders to be economically valuable. In order to investigate further the interactive play between both the variables of knowledge capital and integration, we estimated models (6a)-(6c). In these models, both variables are entered simultaneously as independent explanatory variables, on the reasonable assumption that both measures grasp distinctive features of the firm's knowledge base. Table V reports the results of Eqs.(6a)-(6c).

{TABLE IV ABOUT HERE}

Models (6a) and (6b), which have been constructed along the same lines as Jaffe's (1986) model, perform poorly in terms of the explanatory power of the knowledge variables. While *K/C* and *I/C* are not significant (γ in model 6a and t in model 6b), the significance of the interaction variables ($K/C \cdot i$ in model 6a and $I/C \cdot k$ in model 6b) is significant in the GMM specifications only. Thus, it is neither the stock of knowledge only nor its coherence only that is valued by shareholders. Rather, firms with both a large and a coherent knowledge base enjoy a higher market valuation. The previous remarks should be

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[6] These averages have been calculated using all models (5a) to (5c) and all estimators, where the estimate is found to be significant at the 10% level. Lower levels of significance do not affect the means.

[7] See footnote 6.

treated with caution because the induced multicollinearity between the explanatory variables produced insignificant and inconsistent estimations. Thus, the interpretation advanced is exploratory, and by no means satisfies the more conservative criteria of econometric methods.

More satisfactory is the multiplicative model (6c), which carries the highest explanatory power in four of the least square estimators, namely the OLS, the fixed effect or LSDV, the firm mean or between (BTW) and the autoregressive (AR1) estimators. Most parameter estimates, which in model (6c) are all elasticities, contribute positively and significantly to the firms' stock market value. Our measure of knowledge integration remains significantly different from zero in most regressions. Typically, two firms having an equal patent stock may well be valued differently on the basis of their technological coherence: those having a higher degree of knowledge integration will reach higher market valuations than their less coherent counterparts. In all models where the firm's fixed effect is grasped (LSDV, FD, AR1, FSAR1, AH, GMM1 and GMM2) the estimated elasticity t reduces sharply. This suggests that the measure of knowledge integration is not only stable over time, but also captures a lot of the firm's specificity. A univariate analysis of the variance of *I* shows that two-thirds of the variance is found between rather than within firms. The mean elasticities *ß* and l are to some extent inferior to prior estimations with mean values of approximately .250 and .175.[8] This means that a $1 increase in the firm's profit yields a $3.50 increase in the firm's market value, while a $1 rise in its research spending translates into a $4.85 increase in value. Model (6c) also shows a striking decrease in the average value of a patent. Using the mean value of γ ($\bar{g} = .135$), the average value of a biotechnology patent drops to $16,000.

The previous comments shed doubt on the validity of models (5a), (5b), (5c), (6a) and (6b). Additive linear specification of these models is predominant in most papers dealing with the value of firms' intangible assets. Their advantage is to assume constant returns to scale of the firm's stock market value with respect to its tangible capital. All variations in the firms' valuation become imputable to the firm's intangible assets, provided that we control for other phenomena that may affect the firm's Tobin's q. However, while the elasticities of financial variables *P* and *R* are quite robust from one model to another, we notice that our estimations of the contribution of the knowledge variables *K* and *I* are all the more model dependent, that is, the parameter estimates depend mostly on the functional representation of valuation function. Looking exclusively at the explanatory power of our specification, model (6c) is the best model representing the firms' stock market valuation. It is what we have called the multiplicative model because all stock variables enter the valuation function multiplicatively rather than additively. Similar formulation of models (5a) and (5b), entering the logarithm of the knowledge variables, proved to systematically explain a higher share of the variance of the firm's Tobin's q. The elegance of the logic found in the predominant additive model vanishes when compared to a more conventional Cobb-Douglas representation of the valuation function.

To further address the question of the validity of the model, we explore the robustness of our results using different sub-samples of the original dataset. Table V displays the results

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[8] See footnote 6.

using model (6c). For comparison purposes, the left hand side of table V presents again the results for the whole sample as found in table IV.

{TABLE V ABOUT HERE}

We first test the robustness of the results on the balanced panel. A balanced panel is a panel dataset for which observations are kept for only those firms that are observed every year. Those firms that enter or exit the panel are not kept as observations and we thus introduce a selectivity bias for more stable, surviving firms. 603 observations ($67 \times 9 = 603$) remain. We observe that the parameter estimates of the knowledge variables become insignificant in almost all models, while the financial variables of profit and R&D have inflated parameter estimates. A plausible explanation is that the more stable companies are also large and diversified firms. The short-term performance of larger firms is likely not to be linked to the qualitative characteristics of their knowledge base while the financial results and behaviour of the firms is likely to provide shareholders with vital information on the financial performance of their investment. This also implies that the characteristics of the knowledge base of the remaining firms provide shareholders with key information on their real value, i.e. other than replacement costs.

The above remarks suggest that higher levels of knowledge capital and integration equate with lower survival chances. However, we do not concur with this assessment. Most of the firms that disappear in the time span of our sample were acquired by, or merged with, larger firms. Mergers and acquisitions have increased significantly over the past decade, as they have proved an efficient way to acquire expertise in the realm of biotechnology. Thus our conjecture is that the characteristics of the firm's knowledge base have gained value in the most recent years of the period. Table V tests the presence of such structural change during the period 1989-1997 in two ways. Firstly, we ran the regression for post-1993 observations only. 334 observations were left. As expected, most parameter estimates are inflated, although the extent of this inflation is limited as the F-statistics reveal. This confirms our intuition that the characteristics of the knowledge base have gained momentum as the technology has developed. Firms that have reached higher levels of knowledge capital and knowledge integration are valued more highly on the stock market, and this relationship becomes more relevant when the technology cycle reaches more mature phases. Secondly, we ran similar regressions on post-1993 observations retaining only the stable firms (i.e. those that are present for the whole sample). We achieved 268 ($67 \times 4 = 268$). We observe that the knowledge integration variables remain significant in most models, thus confirming our initial intuition. More profitable and research-intensive firms are highly valued on the stock market. But firms that diversify their knowledge base coherently, that is, firms that exploit complementary technologies, enjoy higher market values than do less coherent firms.

VI. Discussion and Conclusion

Our paper has dealt with the determinants of the market value of biotechnology firms in the period 1989-1997. In particular, we were interested in the role played by the coherence of the knowledge base of firms. We found evidence that the degree of knowledge integration within firms is a significant explanatory variable of firms' stock market value. This means that knowledge integration is economically valuable, as our initial intuition suggested. We found additional evidence that the explanatory power of knowledge integration is at least as great as the variable for knowledge stock. While knowledge stock is indeed important, the way firms combine their technology is equally valuable for shareholders.

As was pointed out in the introduction, the relationship between different components of intangible capital and the market value of firms cannot be considered constant over time. The precise mechanisms and the extent to which given elements of intangible capital contribute to the market value of firms can be expected to vary cyclically and at any given time across industrial sectors. For example, we doubt that our results would apply to mature industries. In this case we would expect firm strategies to switch from knowledge integration to product-market integration in related businesses as technologies moved into later stages of development. Moreover, the mechanisms of knowledge creation and utilisation may vary amongst sectors of *equivalent* knowledge intensity.

There is little systematic knowledge about the relationship of different components of intangible capital to the market value of firms and about their inter-temporal and inter-sectoral variation. We hope that our study makes a valuable contribution to the construction of such knowledge.

On a more methodological note, we found a multiplicative model, similar to a Cobb-Douglas representation of the valuation function, to be more effective than the predominant additive model, although the latter may be may be intellectually more elegant. Our results suggest that while the knowledge variables are not sensitive to the model chosen, their contribution, or impact, changes considerably. The additive model yields estimates that inflate by a factor of 20 the average value of a patent in biotechnology when compared with the more conventional Cobb-Douglas type of model.

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TABLE I.

DESCRIPTIVE STATISTICS FOR SAMPLE REGRESSION (1989-1997, N=709)

Variables	Meaning and measure	Mean	Std.Dev.	Min	Max
V	Stock Market Value[a]	9,006,474.00	1.35×10^7	9,836.70	9.95×10^7
C	Firm's Total assets Value at replacement costs[a]	6,046,695.00	7,460,181.00	4,422.20	3.62×10^7
P	Operating income[a]	620,021.00	920,055.00	-426,524.90	4,510,622.00
RD	Research and Development expenses[a]	324,234.00	389,324.60	858.50	1,918,850
K	Knowledge Stock (Patent Accumulation)	75.60	69.05	2.08	491.53
I	Degree of Knowledge Integration	3.18	5.54	-6.35	35.12835

[a] Thousand of 1990 US dollars.

TABLE II.

LEAST SQUARES REGRESSIONS COMPARING THE EXPLANATORY POWER OF KNOWLEDGE CAPITAL, KNOWLEDGE INTEGRATION, PROFIT, R&D INTENSITY.

DEPENDENT VARIABLE: LOG OF TOBIN'S Q.

Explanatory variable			γ	*t*	*b*	*l*	Standard. Parameter	F-stat. of variable	R^2	Model F	SEE
Knowledge Capital	*K/C*	(1)	596.0 *(.00)*				.173 *(.00)*	39.02 *(.00)*	.402	46.76 *(.00)*	.595
Knowledge Capital	*k*	(2)	.103 *(.00)*				.125 *(.00)*	16.21 *(.00)*	.415	54.54 *(.00)*	.589
Knowledge Integration	*I/C*	(3)		587.3 *(.03)*			.132 *(.03)*	12.17 *(.00)*	.401	46.64 *(.00)*	.595
Knowledge Integration	*i*	(4)		.320 *(.00)*			.200 *(.00)*	29.50 *(.00)*	.426	52.91 *(.00)*	.583
Profit	*p*	(5)			.327 *(.00)*		.290 *(.00)*	79.80 *(.00)*	.463	59.75 *(.00)*	.563
R&D intensity	*r*	(6)				.220 *(.00)*	.293 *(.00)*	44.88 *(.00)*	.437	50.18 *(.00)*	.576

Number of observations: 709. Heteroskedastic-consistent standard errors computed for all regressions. P-values in parentheses. All regressions include a complete set of year and sectoral dummies.

TABLE III.

MARKET VALUATION AS A FUNCTION OF KNOWLEDGE CAPITAL (?), KNOWLEDGE INTEGRATION (*t*), KNOWLEDGE RESOURCES (*f*), PROFIT (*ß*) AND R&D INTENSITY (?).

	Eq.(5a)							Eq.(5b)							Eq.(5c)						
	g	*b*	*l*	R^2	SEE	Sarg	m2	*t*	*b*	*l*	R^2	SEE	Sarg	m2	*f*	*b*	*l*	R^2	SEE	Sarg	m2
OLS	.061 *(.57)*	.301 *(.00)*	.179 *(.00)*	.488	.551	-	-	-.045 *(.62)*	.297 *(.00)*	.185 *(.00)*	.488	.551	-	-	.010 *(.07)*	.303 *(.00)*	.174 *(.00)*	.490	.549	-	-
LSDV	.219 *(.02)*	.211 *(.03)*	.206 *(.00)*	.135	.386	-	-	.329 *(.00)*	.218 *(.02)*	.214 *(.00)*	.144	.384	-	-	.014 *(.02)*	.221 *(.02)*	.209 *(.00)*	.136	.386	-	-
BTW	-.062 *(.82)*	.269 *(.00)*	.221 *(.00)*	.683	.415	-	-	-.393 *(.26)*	.264 *(.00)*	.233 *(.00)*	.688	.411	-	-	.003 *(.88)*	.274 *(.00)*	.215 *(.00)*	.682	.414	-	-
FD	.228 *(.14)*	.131 *(.10)*	108 *(.22)*	.166	.340	-	-	.078 *(.30)*	.132 *(.10)*	.128 *(.15)*	.164	.340	-	-	.009 *(.51)*	.133 *(.09)*	.130 *(.15)*	.162	.341	-	-
AR1	.242 *(.07)*	.217 *(.00)*	.135 *(.08)*	.139	.314	-	-	.276 *(.00)*	.221 *(.00)*	.156 *(.05)*	.141	.314	-	-	.014 *(.07)*	.224 *(.00)*	.147 *(.06)*	.138	.315	-	-
FSAR	.199 *(.05)*	.188 *(.01)*	.197 *(.10)*	.203	.286	-	-	.248 *(.00)*	.190 *(.00)*	.212 *(.05)*	.205	.286	-	-	.010 *(.25)*	.197 *(.00)*	.207 *(.06)*	.194	.287	-	-
AH	.290 *(.06)*	.065 *(.59)*	.409 *(.00)*	.226	.299	-	-	.098 *(.55)*	.078 *(.52)*	.441 *(.00)*	.252	.300	-	-	.051 *(.00)*	.086 *(.48)*	.315 *(.00)*	.255	.299	-	-
GMM1	.126 *(.37)*	.490 *(.01)*	.236 *(.02)*	-	.345	288.1 *(.00)*	-2.25 *(.02)*	.269 *(.00)*	.445 *(.00)*	.219 *(.00)*	-	.351	251.3 *(.00)*	-1.94 *(.05)*	.053 *(.00)*	.556 *(.00)*	.193 *(.06)*	-	.341	279.7 *(.00)*	-1.78 *(.07)*
GMM2	.159 *(.05)*	.542 *(.00)*	.292 *(.00)*	-	.347	73.2 *(.96)*	-1.22 *(.22)*	.293 *(.00)*	.439 *(.00)*	.231 *(.00)*	-	.351	74.70 *(.48)*	-1.19 *(.25)*	.054 *(.00)*	.594 *(.00)*	.227 *(.00)*	-	.363	75.14 *(.94)*	-.87 *(.39)*

The OLS, LSDV, AR and PSAR models have 709 observations. The BTW (group means) model has 84 observations. The FD (first difference) model has 625 observations. The AH, GMM1 and GMM2 models have 374 observations using three lags. All models include year dummy variables. The OLS, BTW, AR1, FSAR1, AH, GMM1 and GMM2 include industry dummy variables. In GMM1 and GMM2, all explanatory variables are considered as predetermined, while the year dummy variables are entered as instruments. All standard errors are adjusted for panel heteroskedasticity using the White's correction. The parameter g, t and f have been multiplied by 10^{-3} for convenience only.

TABLE IV.
MARKET VALUATION AS A FUNCTION OF KNOWLEDGE CAPITAL (?), KNOWLEDGE INTEGRATION (*t*), PROFIT (ß) AND R&D INTENSITY (?).

	Eq.(6a)							
	g	*t*	*b*	*l*	R^2	SEE	Sarg	m2
OLS	-.732 *(.07)*	.274 *(.04)*	.297 *(.00)*	.178 *(.00)*	.491	.550	-	-
LSDV	-.365 *(.42)*	.195 *(.19)*	.221 *(.02)*	.212 *(.00)*	.136	.386	-	-
BTW	-.380 *(.79)*	.117 *(.82)*	.269 *(.00)*	.218 *(.00)*	.683	.417	-	-
FD	-.264 *(.84)*	.172 *(.69)*	.134 *(.09)*	117 *(.17)*	.168	.340	-	-
AR1	-.455 *(.62)*	.237 *(.41)*	.227 *(.01)*	.145 *(.06)*	.143	.314	-	-
FSAR1	-.009 *(.99)*	.068 *(.79)*	.194 *(.01)*	.201 *(.08)*	.198	.286	-	-
AH	-3.64 *(.00)*	1.40 *(.00)*	.068 *(.56)*	.438 *(.00)*	.243	.292	-	-
GMM1	-3.76 *(.00)*	1.43 *(.00)*	.522 *(.00)*	.233 *(.02)*	-	.336	309.8 *(.00)*	-1.68 *(.09)*
GMM2	-3.53 *(.00)*	1.37 *(.00)*	.580 *(.00)*	.274 *(.00)*	-	.338	75.3 *(.99)*	-1.11 *(.27)*

	Eq.(6b)							
	g	*t*	*b*	*l*	R^2	SEE	Sarg	m2
OLS	.036 *(.89)*	-.144 *(.85)*	.298 *(.00)*	.185 *(.00)*	.487	.551	-	-
LSDV	-.146 *(.41)*	7.22 *(.08)*	.215 *(.02)*	.217 *(.00)*	.145	.384	-	-
BTW	.616 *(.22)*	-2.09 *(.33)*	.271 *(.00)*	.216 *(.01)*	.691	.412	-	-
FD	.337 *(.35)*	-.730 *(.42)*	.135 *(.09)*	111 *(.24)*	.166	.340	-	-
AR1	.114 *(.65)*	.028 *(.97)*	.222 *(.01)*	.149 *(.05)*	.141	.314	-	-
FSAR1	-.052 *(.83)*	.111 *(.85)*	.193 *(.01)*	.211 *(.05)*	.206	.287	-	-
AH	1.79 *(.00)*	-4.73 *(.00)*	.076 *(.53)*	.432 *(.00)*	.229	.296	-	-
GMM1	2.63 *(.00)*	-7.23 *(.00)*	.455 *(.01)*	.356 *(.00)*	-	.330	397.6 *(.00)*	-2.21 *(.02)*
GMM2	2.66 *(.00)*	-7.30 *(.00)*	.495 *(.00)*	.330 *(.00)*	-	.332	76.30 *(.54)*	-1.16 *(.24)*

	Eq.(6c)							
	g	*t*	*b*	*l*	R^2	SEE	Sarg	m2
OLS	.119 *(.00)*	.440 *(.00)*	.325 *(.00)*	.175 *(.00)*	.540	.522	-	-
LSDV	.141 *(.00)*	.150 *(.01)*	.185 *(.05)*	.211 *(.00)*	.149	.384	-	-
BTW	.105 *(.07)*	.660 *(.00)*	.323 *(.00)*	.204 *(.00)*	.747	.372	-	-
FD	.146 *(.07)*	.060 *(.46)*	.133 *(.09)*	.134 *(.13)*	.166	.341	-	-
AR1	.175 *(.00)*	.125 *(.05)*	.191 *(.02)*	.143 *(.07)*	.151	.312	-	-
FSAR1	.142 *(.00)*	.083 *(.28)*	.172 *(.01)*	.190 *(.10)*	.203	.287	-	-
AH	.042 *(.73)*	.085 *(.37)*	.024 *(.88)*	.308 *(.00)*	.220	.307	-	-
GMM1	.060 *(.72)*	. 200 *(.10)*	.298 *(.12)*	.166 *(.09)*	-	.347	270.6 (.00)	-1.71 (.09)
GMM2	.111 *(.04)*	. 152 *(.01)*	.360 *(.00)*	.174 *(.00)*	-	.363	74.11 (.99)	-1.14 (.25)

The OLS, LSDV, AR and PSAR models have 709 observations. The BTW (group means) model has 84 observations. The FD (first difference) model has 625 observations. The AH, GMM1 and GMM2 models have 374 observations using three lags. All models include year dummy variables. The OLS, BTW, AR1, FSAR1, AH, GMM1 and GMM2 include industry dummy variables. In GMM1 and GMM2, all explanatory variables are considered as predetermined, while the year dummy variables are entered as instruments. All standard errors are adjusted for panel heteroskedasticity using the White's correction. The parameter g and t in Eq.(6a) and Eq.(6b) have been multiplied by 10^{-3} for convenience only.

TABLE V.
TESTING FOR STABILITY USING MODEL 6C

	Unbalanced Panel N = 709					Balanced Panel N = 603					Panel > 1993 N = 334					Balanced Panel > 1993 N = 268				
	g	*t*	*b*	*l*	F (*p-va*)	*g*	*t*	*b*	*l*	F (*p-va*)	*g*	*t*	*b*	*l*	F (*p-va*)	*g*	*t*	*b*	*l*	F (*p-va*)
OLS	.119	.440	.325	.175	-	.088	.392	.328	.203	3.45	.098	.514	.454	.122	26.2	.089	.532	.456	.158	46.95
	(.00)	*(.00)*	*(.00)*	*(.00)*		*(.00)*	*(.00)*	*(.00)*	*(.00)*	*(.00)*	*(.00)*	*(.00)*	*(.00)*	*(.00*	*(.06)*	*(.01)*	*(.00)*	*(.00)*	*(.01)*	*(.00)*
LSDV	.141	.150	.185	.211	-	.121	.056	.305	.281	5.61	.246	.141	.389	-.085	29.45	.192	.064	.677	.282	23.66
	(.00)	*(.01)*	*(.05)*	*(.00)*		*(.03)*	*(.33)*	*(.05)*	*(.00)*	*(.00)*	*(.05)*	*(.09)*	*(.13)*	*(.38)*	*(.00)*	*(.10)*	*(.53)*	*(.00)*	*(.04)*	*(.00)*
FD	.146	.060	.133	.134	-	.090	-.042	.174	.267	4.37	.200	.046	.163	.206	.398	.138	.058	.192	.622	3.35
	(.07)	*(.46)*	*(.09)*	*(.13)*		*(.31)*	*(.51)*	*(.02)*	*(.01)*	*(.00)*	*(.06)*	*(.69)*	*(.23)*	*(.16)*	(.98)	*(.22)*	*(.60)*	*(.12)*	*(.00)*	(.00)
AR1	.175	.125	.191	.143	-	.158	.007	.272	.262	5.32	.200	.226	.287	.230	1.39	.162	.152	.428	.520	6.70
	(.00)	*(.05)*	*(.02)*	*(.07)*		*(.05)*	*(.89)*	*(.00)*	*(.00)*	*(.00)*	*(.01)*	*(.03)*	*(.10)*	*(.06)*	*(.18)*	*(.11)*	*(.10)*	*(.00)*	*(.00)*	*(.00)*
FSAR	.142	.083	.172	.190	-	.116	-.018	.262	.288	4.82	.142	.160	.267	.177	2.93	.027	.115	.504	.473	9.18
	(.00)	*(.28)*	*(.01)*	*(.10)*		*(.05)*	*(.79)*	*(.02)*	*(.00)*	*(.00)*	*(.01)*	*(.07)*	*(.00)*	*(.23)*	*(.00)*	*(.72)*	*(.09)*	*(.00)*	*(.00)*	*(.00)*
AH	.042	.085	.024	.308	-	-.048	.019	.049	.418	-	.231	.120	.252	.223	-	.225	.089	.374	.502	-
	(.73)	*(.37)*	*(.88)*	*(.00)*		*(.69)*	*(.83)*	*(.66)*	*(.00)*		*(.20)*	*(.39)*	*(.23)*	*(.05)*		*(.22)*	*(.47)*	*(.04)*	*(.00)*	
GMM1	.060	. 200	.298	.166	-	-.199	. 090	.355	.330	-	.135	. 232	.202	.111	-	-.115	. 054	.280	.395	-
	(.72)	*(.10)*	*(.12)*	*(.09)*		*(.13)*	*(.40)*	*(.02)*	*(.00)*		*(.43)*	*(.18)*	*(.38)*	*(.34)*		*(.26)*	*(.68)*	*(.12)*	*(.00)*	
GMM2	.111	. 152	.360	.174	-	-.154	. 173	.207	.335	-	.050	. 240	.238	.122	-	-.099	.101	.251	.500	-
	(.04)	*(.01)*	*(.00)*	*(.00)*		*(.13)*	*(.10)*	*(.04)*	*(.00)*		*(.56)*	*(.00)*	*(.00)*	*(.00)*		*(.39)*	*(.09)*	*(.00)*	*(.00)*	

The OLS, LSDV, AR and PSAR models have 709 observations. The BET (group means) model has 84 observations. The FD (first difference) model has 625 observations. GMM1 and GMM2 have 457 observations using two lags. All models include year dummy variables, and industry dummy variables when the variables are entered in levels (OLS, BET, GMM1 and GMM2). In GMM1 and GMM2, the financial variables are considered endogenous while the variables characterising the firms' knowledge base are entered as predetermined. The year dummy variables are entered as instruments in the GMM specifications. All standard errors are adjusted for panel heteroskedasticity using the White's correction.

APPENDIX A

A particularly important question in using GMM estimators is the endogeneity of the explanatory variables. This challenges the conventional wisdom that the firm's set of characteristics (its profit, its research intensity, its knowledge stock and level of integration) drives its market value but that the reverse is not true. With increased access to information, shareholders and other institutional investors may well have an effect on the firm's decisions in the short run, thus influencing future levels of R&D investment, ultimate profit and knowledge characteristics. In other words, these potential reverse relationships between the dependent and explanatory variables suggest that the latter are likely to behave as endogenous variables.

To address the potential endogeneity, predeterminedness or exogeneity of the explanatory variables, we perform a Granger test for causality. Granger's notion of causality states that *x* Granger causes *q* if we are better able to predict *q* using lagged values of *x* and lagged values of *q*. In the presence of endogenous variables, a feedback loop is expected to occur, such that *x* causes *q* and, symmetrically, that *q* causes *x*. If we observe that *x* causes *q* but *q* does not cause *x*, this latter variable *x* is meant to be predetermined. The test for causality is performed by estimating the following system:

$$\begin{cases} q_{nt} = \sum_{s=1}^{p} d_{1,s} x_{n,t-s} + \sum_{s=1}^{p} r_{1,s} q_{n,t-s} + j_{1,t} + e_{1,nt} & \text{(1A)} \\ x_{nt} = \sum_{s=1}^{p} d_{2,s} x_{n,t-s} + \sum_{s=1}^{p} r_{2,s} q_{n,t-s} + j_{2,t} + e_{2,nt} & \text{(2A)} \end{cases}$$

where *x* is the log of any of the variables *K*, *I*, *?* and *R*, and thus $d = \{g, t, b, l\}$. Because Granger causality tests are sensitive to the chosen lags, we present the results for different lag structures, where $p = 2$ to $p = 4$. The choice of a maximum of four lags is dictated by the size of the sample and the availability of a sufficient number of observations. The results are reported in table III. On the left-hand side of the table, results for Eq.(1A) are reported. On the right-hand side of the table, results for Eq.(2A) are reported. For each estimation, evidence of the validity of instruments (Sargan specification test), the first and second order test for autocorrelation of the residuals (m1 and m2, respectively) is reported. The joint significance test of $?^2$ refers to the causality test "does *x* Granger cause *q*?" for Eq.(1A) and "does *q* Granger cause *x*?" for Eq.(2A). The last column of table III, shows the direction of the Granger causality.

{TABLE T1A ABOUT HERE}

Table III presents strong evidence of the endogeneity of the currency-based variables of research intensity and profit. This reflects the fact that the current valuation of firms by the market is quite likely to influence current and future decisions such as investment in R&D. This offers essential insights into the decision making process of firms. Of particular importance is that firms may decide on higher levels of R&D investment to capitalise on their current valuation rather than to benefit from expected revenues derived from future innovations. Note that this may well reconcile the inherent dilemma of firms as to whether to explore future avenues of research or to exploit their current technologies. Further probing of such an interpretation would require additional insights from the firms themselves, for little can be concluded from the available data.

The behaviour of the knowledge variables is rather different. No evidence of endogeneity is found when allowing for a two-year or three-year lag: the valuation of firms by the market is not likely to affect future levels of knowledge stocks or integration. The reverse causation applies however: current levels of knowledge stocks and integration do affect the current valuation of the firm by the market. This is consistent with the fact that knowledge acquisition and integration is particularly time demanding. In fact, there is a considerable level of irreversibility in the technological strategies pursued by firms. While the characteristics of the firms' knowledge base do affect the current valuation of firms, changes in the value of the firm are likely to affect the degree of knowledge integration over a four-year time period. Examples of such shocks are the release of the human genome into the public domain, affecting the market value of firms such as Celera, which had relied extensively on appropriating returns from human genetic sequences. Our results suggest that *ceteris paribus*, recovering previously achieved levels of market valuation is likely to take on average, four years.

The discussion should be read with caution. The most consistent specification occurs when allowing for three lags only, for which we can safely reject the null hypothesis of second order autocorrelation of the residuals (m2). There is, however, little evidence of the validity of instruments (Sargan Test) for Eqs.(1A) and (2A), while second-order autocorrelations arise when allowing for two-year and four-year lags. In the face of little evidence of endogeneity and predeterminedness, we would adopt the milder assumption of predeterminedness of all the explanatory variables in the subsequent GMM regressions.

TABLE T1A.
GRANGER CAUSALITY TESTS.

	Eq.(1A) Market value as dependent				Eq.(2A) Market value as explanatory				Granger Causality
	Lags (2). N=457								
	Sarg.	m1	m2	?$_2$	Sarg.	m1	m2	?$_2$	
Knowledge Capital	58.0 *(.005)*	-3.05 *(.002)*	-2.74 *(.006)*	12.92 *(.006)*	16.06 *(.327)*	-1.62 *(.105)*	.94 *(.345)*	5.18 *(.159)*	$k \rightarrow q$
Knowledge Integration	58.7 *(.004)*	-3.11 *(.001)*	-2.43 *(.015)*	16.0 *(.001)*	22.7 *(.359)*	1.12 *(.264)*	.66 *(.508)*	4.16 *(.125)*	$i \rightarrow q$
Profit	58.5 *(.004)*	-3.26 *(.001)*	-2.74 *(.006)*	4.6 *(.201)*	38.7 *(.227)*	-2.74 *(.006)*	-1.31 *(.197)*	33.21 *(.000)*	$p \leftarrow q$
R&D intensity	58.3 *(.004)*	-3.10 *(.001)*	-3.52 *(.004)*	24.8 *(.000)*	62.3 *(.002)*	-2.38 *(.002)*	-1.36 *(.175)*	13.73 *(.003)*	$r \leftrightarrow q$
	Lags (3). N = 374								
	Sarg.	m1	m2	?$_2$	Sarg.	m1	m2	?$_2$	
Knowledge Capital	52.9 *(.006)*	-2.87 *(.004)*	-1.19 *(.233)*	21.7 *(.000)*	34.9 *(.106)*	-1.72 *(.085)*	-1.42 *(.154)*	3.98 *(.408)*	$k \rightarrow q$
Knowledge Integration	56.9 *(.002)*	-2.91 *(.003)*	-.82 *(.413)*	10.3 *(.035)*	39.0 *(.126)*	-4.70 *(.000)*	-2.73 *(.006)*	3.52 *(.474)*	$i \rightarrow q$
Profit	57.5 *(.002)*	-2.98 *(.002)*	-1.16 *(.248)*	9.94 *(.041)*	34.6 *(.258)*	-2.13 *(.033)*	-1.48 *(.140)*	12.95 *(.012)*	$p \leftrightarrow q$
R&D intensity	48.8 *(.017)*	-2.48 *(.013)*	-1.62 *(.104)*	130.8 *(.000)*	52.0 *(.008)*	-.82 *(.413)*	-.71 *(.480)*	65.63 *(.000)*	$r \leftrightarrow q$
	Lags (4). N = 292								
	Sarg.	m1	m2	?$_2$	Sarg.	m1	m2	?$_2$	
Knowledge Capital	43.2 *(.018)*	-2.63 *(.008)*	3.34 *(.000)*	24.52 *(.000)*	26.0 *(.461)*	-.14 *(.89)*	-1.37 *(.169)*	9.78 *(.082)*	$k \leftrightarrow q$
Knowledge Integration	46.7 *(.009)*	-2.50 *(.004)*	3.79 *(.000)*	28.5 *(.062)*	29.2 *(.299)*	-1.08 *(.278)*	-1.17 *(.248)*	47.45 *(.001)*	$i \leftrightarrow q$
Profit	46.0 *(.009)*	-2.91 *(.004)*	3.72 *(.000)*	44.8 *(.000)*	30.1 *(.265)*	-2.45 *(.015)*	-1.92 *(.053)*	17.79 *(.003)*	$p \leftrightarrow q$
R&D intensity	46.3 *(.008)*	-1.74 *(.082)*	2.24 *(.025)*	150.5 *(.000)*	46.7 *(.007)*	-3.00 *(.003)*	-2.13 *(.034)*	70.62 *(.000)*	$r \leftrightarrow q$

GMM two-step estimator. The explanatory variables x and q are entered as endogenous. All estimations include year dummy variables, entered as instruments in the GMM specifications.
P-values in parentheses.