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Technological diversification, coherence and performance of firms

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Abstract

Technological diversification at the level of the firm, i.e. the expansion of a firm's technology base into a wide range of technology fields, is found to be a prevailing phenomenon in all three major industrialized regions: US, Europe and Japan, prompting the term multi-technology corporation. Whereas previous studies have provided insights into the composition of technology portfolios of multi-technology firms, little is known about the link between technological diversification and firms' technological performance. Against a backdrop of the technology and innovation management literature, this article investigates the relationship between technological diversification and technological performance, taking into account the moderating role of technological coherence in firms' technology portfolios. Hereby, technological coherence is defined as the degree to which technologies in a technology portfolio are technologically related. In order to measure the technological coherence of portfolios, a measure of technological relatedness of technology fields is constructed based on patent citation patterns found in 450,000 EPO patent grants. Two hypotheses are presented in this article: (1) Technological diversification has an inverted U-shaped relationship with technological performance; and (2) Technological coherence moderates the relationship between technological diversification and technological performance positively. These hypotheses are tested empirically using a panel dataset (1995-2003) on patent portfolios pertaining to 184 US, European, and Japanese firms. The firms selected are the largest R&D actors in five industries: Pharmaceuticals & Biotechnology, Chemicals, Engineering & General Machinery, IT Hardware (computers and communication equipment), and Electronics & Electrical Machinery. Empirical results, obtained by fixed-effects negative binomial regressions, support both hypotheses in this article. Technological diversification has an inverted U-shaped relationship with technological performance. While technological diversification offers opportunities for cross-fertilization and technology fusion, high levels of diversification may yield few marginal benefits as firms risk lacking sufficient levels of scale to benefit from wide-ranging technological capabilities, and firms may encounter high levels of coordination and integration costs. Further, the results show that the net benefits of technological diversification are higher in technologically coherent technology portfolios. If firms build up a technologically coherent diversified portfolio, the presence of sufficient levels of scale is ensured and coordination costs are limited. This article clearly identifies the important role of technological coherence and points out in the discussion session the relevance of future research on interface management practices directed to the realization of the benefits of technological diversification.

Introduction

Innovation is not only one of the driving forces behind welfare creation at the level of regions and nations; it has also been acknowledged as crucial to the long-term survival and growth of the firm (e.g. Schumpeter, 1934: Van de Ven, et al. 1989, 1999; Tushman and Anderson, 1997; Baumol, 2002). Hence, firms build up and/or acquire knowledge in different technology fields, resulting in technology portfolios which can vary in terms of technological diversification and technological coherence. Technology portfolios in which knowledge is spread over many technology fields are considered as signaling higher levels of technological diversification. When the different technology fields share a similar underlying knowledge base, a firm's technology portfolio is considered as technologically coherent. While technological coherence is greatest for focused (non-diversified) technology portfolios, it can and does differ widely between firms that have equally diversified technology portfolios. The impact of these varying degrees of coherence on the relationship between technological diversification and technological performance at the firm level has received scant attention to date[1].

Drawing on insights from the technology and innovation management literature, this article examines the relationship between technological diversification and technological performance, in conjunction with the technological coherence of firms' technology portfolios. The next section provides an overview of the existing literature on technological diversification and coherence, which allows us to advance the two hypotheses of this article. These focus on the curvilinear relationship between technological diversification and technological performance, on the one hand, and the moderating role of technological coherence on this relationship, on the other. Next, the data, indicators and methods used to assess empirically the central constructs of the paper are discussed. In order to measure the technological coherence of portfolios, a measure of technological relatedness of technology fields is constructed based on patent citation patterns found in approximately 450,000 granted patents. The article finishes with a results section and a discussion of the major findings. Directions for future research are also suggested.

Theory and Hypotheses

Large firms' technology portfolios tend to be highly diversified, and technological diversification levels exceed diversification levels of product portfolios (Gambardella and Torrisi, 1998; Pavitt et al, 1989; Patel and Pavitt, 1997). Several reasons have been advanced to explain the technological diversity of large firms' technology portfolios. One driving force is the increasing complexity of products and production processes over time (Rycroft and Kash, 1999), making it necessary for companies to invest in a variety of technology fields. This investment remains a necessity, even in the presence of technological outsourcing as effective assimilation of externally acquired technologies requires the presence of 'absorptive capacity' (Cohen and Levinthal, 1989; Granstrand, Patel and Pavitt, 1997)[2]. Second, firms explore and experiment with new technologies to learn about their commercial potential, which is rarely clear immediately after a new scientific or technological breakthrough occurs (Patel and Pavitt, 1997). The widespread practice of pharmaceutical firms, whose core competencies in the past resided in chemistry, to experiment with biochemical and biological technologies can be seen as an example. Third, as advanced by Penrose (1959), firms learn to use their resources (such as R&D capabilities) more efficiently over time, which leads to the creation of excess resources. Since R&D capabilities are often specific in nature, high transaction costs are associated with exploiting them in arm's length markets. Hence, firms may use these excess resources to diversify into promising new technologies.

The drivers of technological diversification present themselves partly as industry-specific as demonstrated by Stephan (2002). He finds that pharmaceutical and telecom firms have technology portfolios which are on average considerably less diverse than those of firms within the automotive, electric engineering, chemical or material industries. Yet, considerable variance in technological diversification levels remains among firms within the same sector. This variance reflects the different bets made by management in the face of technological complexity and uncertainty (Nelson and Winter, 1977; Patel and Pavitt, 1997). At the same time, there is a high persistency over time in the composition of firms' technology portfolios which can be related to the nature of the innovation process that takes place within firms. Innovation can be defined as a cumulative process of incremental problem definition and solving activities (Rosenberg 1982). As many problems are firm-specific, a firm's learning experience is distinctive. Due to the distinctiveness and cumulativeness of a firm's learning experience, its technological trajectory can be characterized as unique and path-dependent (Dosi, 1982; Garud and Karnoe, 2002). Consequently, firms' current technology portfolios

are, at least partly, a reflection of their past problems, interests and capabilities. Fai (2003) and Cantwell (2004) have found that, even over time periods of 100 years, most firms continue to develop competencies in technology fields in which they gained their initial technological competencies.

Hypotheses

Several potential positive effects of technological diversification on the technological performance of firms can be pointed out. Firms building up knowledge in multiple fields create the potential to cross-fertilize, yielding new inventions and functionalities and/or increased product and process performances (Granstrand, 1998)[3]. Closely related, a broad technology base may enable firms to create completely new products and services resulting from the combination of knowledge from different technology fields (Argyres, 1996; Hargadon, 1997; Kodama, 1992). According to Kodama (1992), the impact of so-called 'technology fusion' innovations has become more and more important over time. The rise of mechatronics, implying a 'fusion' of knowledge in electronic, mechanical and materials technologies, is a case in point[4]. Recent empirical evidence by Nesta and Saviotti (2005) and Garcia-Vega (2006) has confirmed a general positive impact of technological diversification on firms' technological performance[5].

Technological diversification is, however, not costless. First, it may prevent firms from creating the focus needed to develop sufficiently strong capabilities in any specific technology domain, necessary to realize economies of scale in technology development. Second, firms with a technologically diversified portfolio are likely to bear larger integration, coordination and communication costs (Granstrand, 1998). These additional coordination costs arise in particular when diversifying firms try to combine more mature technologies with novel, emerging technologies that might conflict with the dominant core technologies of the firm. In line with the notion of creative destruction, advanced by Schumpeter in the mid-1930s, several scholars have pointed to the tensions that organizations encounter when organizing exploitation (of mature technologies) and exploration (of emerging technologies) simultaneously.[6] Such tensions are experienced especially by 'incumbent firms' as they put in place multiple resources and capabilities aimed at exploitation. The very presence of these resources might hamper engaging in activities of a more explorative nature (Leonard-Barton, 1992). Abernathy (1991) argued that it is almost impossible for an organization to be simultaneously creative and productive. In addition, both activities do differ in terms of their

contribution to the competitive advantage of a firm, depending on the stage a technology and/or industry finds itself in: whereas creativity can be seen as highly relevant during the pre-dominant design – exploration-oriented – phase; productivity dominates during post-dominant design – exploitation-oriented – phase (Abernathy and Utterback, 1978; Anderson and Tushman, 1991). Along similar lines, Ghemawat (1991) – adopting a game-theoretic perspective – points to the irreconcilable nature of 'flexibility' and 'commitment'. As long as exploration is a priority, one needs to remain flexible from an organizational point of view. Once committed, i.e. once a firm has adopted a determined exploitation trajectory, flexibility is at odds with the dominant mode of organization required for exploitative purposes. Ghemawat argues that this duality of 'flexibility' versus 'commitment' is extremely difficult to handle and to maintain simultaneously within an organization. More recently, Benner and Tushman (2003) also point to these tensions when discussing the impact of process management activities on exploitation and exploration trajectories.

The above suggests a complex, non-linear relationship between the level of technological diversification and firms' technological performance. While technological diversification offers opportunities for cross-fertilization and technology fusion, higher levels of technological diversification may yield fewer marginal benefits as firms risk lacking sufficient levels of scale to benefit sufficiently from wide-ranging technological diversification. In addition, coordination and integration costs may increase exponentially with higher levels of technological diversification, as more diversified firms are more likely to encounter difficulties in combining mature (exploitative) technologies with explorative trajectories. This leads to the following hypothesis:

Hypothesis 1: Technological diversification has an inverted U-shaped relationship with technological performance.

As outlined above, when implementing technological diversification strategies, firms may encounter situations in which they have to find ways to handle the tensions between exploiting existing technological trajectories and exploring new technologies. Recently, several scholars have advanced the notions of semi- or quasi-structures (Schoonhoven and Jellinek, 1990; Brown and Eisenhardt, 1997) and ambidextrous organizations (Tushman, Anderson and O'Reilly, 1997; Benner and Tushman, 2003, O'Reilly and Tushman, 2004) to handle the opposing requirements. An additional moderator of the organizational and

managerial complexities encountered – besides organizational design choices – might be found in the level of synergetic potential in a firm's technology portfolio. Diversified firms might be able to outperform focused or less diversified firms when technological relatedness allows such synergies to be enacted (Van Looy, Martens and Debackere, 2005). Stated otherwise, the potential for synergy might be dependent on the technological coherence of a firm's technology portfolio. A technology portfolio is considered technologically coherent when it combines technologies that share a common knowledge base, rely upon common scientific principles or have similar heuristics of search (Breschi, Lissoni and Malerba, 2003). Firms that diversify their technology portfolio in a technologically coherent way may be able to attenuate the potential negative impact of technological diversification: coherence implies the presence of sufficient scale and facilitates coordination and communication (Allen, 1977; Peltz and Andrews, 1967). At the same time, technologically coherent diversification is likely to put firms in a better position to enact the cross-fertilization potential offered by their presence in a variety of technology fields. Therefore, the following is hypothesized:

Hypothesis 2: The higher the degree of technological coherence in a firm's technology portfolio, the greater the positive impact of technological diversification on technological performance.

Data and Methods

Data

In order to investigate the impact of technological diversification and coherence on firms' technological performance, a panel data set is built up. This data set contains information on patent applications from 184 European, US, and Japanese firms that are active in 5 industries: (1) Engineering & General Machinery, (2) Pharmaceuticals & Biotech, (3) Chemicals, (4) IT Hardware (computers and communication equipment), and (5) Electronics & Electrical Machinery. The firms selected are the top R&D spenders in their region of origin and industry as indicated by the '2004 EU Industrial R&D Investment Scoreboard'. The resulting sample contains roughly the same number of firms in each industry for each region of origin (Table 1). The sample firms are observed over 9 years (1995-2003).

INSERT TABLE 1

Patent application data are used as an indicator of a firm's technological performance and to construct technological diversification and coherence measures. Compared to other technology indicators, the use of patent data has several advantages: (1) they are easily available at the level of the firm (2) they cover fairly long time series and (3) they provide detailed information on the technological content of a firm's innovation activities. Disadvantages of working with patent data include the poor coverage of software innovations (particularly important in the IT sector) and varying patent propensities among industries and, to a lesser extent, firms[7] (Griliches, 1990). While patent grants are more reliable indicators of innovations, our dataset is constructed based on patent applications. Patent granting decisions in the European Patent Office, our source of patent data, take on average 4 years, making patent grants a poor indicator of recent innovation activities of firms.

Patent data are collected at the consolidated level, i.e. all patents assigned to the parent firm as well as consolidated (majority-owned) subsidiaries of the parent firm are taken into account to assess the technological performance, diversification, and coherence of the sample firms. For this purpose, yearly lists of subsidiaries included in annual reports, yearly 10-K reports filed with the SEC in the US and, for Japanese firms, information on foreign subsidiaries published by Toyo Keizai in the yearly Directories of Japanese Overseas Investments, are used. The consolidation was performed on a yearly basis since the group structures of parent firms may change substantially over time due to acquisitions, mergers, de-mergers, and spin-offs. Constructing 'consolidated' patent portfolios is important since on average 20 percent of the patents in the patent portfolios of parent firms are not applied under the (current) name of the parent firm (Magerman et al, 2005).

The consolidated patent portfolios of parent firms are constructed on the basis of a moving time window of 5 years. Hence, the consolidated patent portfolio of a parent firm in year i consists of all patent applications in the past five years by the entities that were part of the parent firm in year i. Such a moving window of five years allows for a reliable measurement of the levels of technological coherence and technological diversification in firm patent portfolios and has been found an appropriate time frame for assessing technological impact in high-tech industries (Vanhaverbeke, Duysters and Beerkens, 2002).

Dependent variable and Estimation Method

The dependent variable, PATENT, is the yearly number of firm EPO patent applications over the time period 1995-2003. Since the dependent variable takes only non-negative integer values, a negative binomial panel data fixed effects model is employed. This panel data estimation technique controls for the impact of unobserved firm-specific characteristics on firms' technological performance (characteristics that may correlate with, and bias the effect of the explanatory variables, if not controlled for).

Technological diversification

All patents contain one or more technology field codes (IPC classification), which are given by the patent examiners of EPO. Each of those 8-digit IPC codes (+- 64000) stands for a particular technical function or application (OECD, 1994). This article uses a technology-oriented classification that assigns each IPC code to one of 30 different technology fields. This classification has been elaborated jointly by Fraunhofer-Gesellschaft-ISI, Institut National de la Propriété Industrielle (INPI) and Observatoire des Sciences and des Techniques (OST) and is reported in Appendix 1. The technology class information of the patents in a firm's patent portfolio is used to derive measures of technological diversification and technological coherence. Technological diversification is defined as the spread of the patent portfolio over technology classes. Let N_i denote the number of patents in the technology portfolio of a certain firm that are assigned to technology class i, such that $N = \Sigma_i N_i$. Technological diversification is then defined as:

$$DIV = 1 / (\Sigma_i (N_i/N)^2)$$

This definition is a transformation of the so-called Herfindahl index ($\Sigma_i (N_i/N)^2$). The Herfindahl index measures the degree of concentration of patents among patent classes. It takes the value 1 if firms have patents in a single class only, and approaches zero if patents are evenly dispersed over a large number of technology fields. This variable is a more accurate measurement of technological diversification than a simple count of technologies in a firm's knowledge base, since the latter is very sensitive to accidental discoveries in particular technology fields. The variable DIV transforms the Herfindahl measure into a measure of diversification by taking the inverse. The index is usually termed the 'equal distribution number equivalent' of the Herfindahl index: the value represents the number of technology fields over which patents would have to be equally distributed in order to generate

the same value of the equal distribution number equivalent. In the case of the above-mentioned technology classification, the minimum value is 1 and the theoretical maximum is 30. For example, if a firm has a portfolio of 100 patents, which are equally spread among 10 technology classes, the Herfindahl index is 0.1 and the diversification index DIV is equal to 10. If, however, among the 10 classes, patents are largely concentrated in one or two classes, the level of diversification DIV drops below 10. For instance, if two classes have 30 patents, and the remaining 8 each have 5, the Herfindahl index is 0.2 and the index DIV is 5: the distribution of patents leads to the same DIV index as an equal distribution of the 100 patents over 5 classes.

In order to test for a non-linear relationship between technological diversification and technological performance, both the linear (DIV) and squared (DIV^2) term of technological diversification are included in the empirical model. As stated in hypothesis 1, a positive sign for DIV and a negative sign for DIV^2 are expected.

Technological Coherence

Technological coherence is defined as the degree to which technologies share the same underlying knowledge base ('technologically-related' technologies). In order to calculate the technological coherence of a firm's patent portfolio, one needs, for each pair of technology classes in a patent portfolio, a measure of the level of technological-relatedness. The most common approach to constructing such a measure is to examine technological information available in patent databases. The approach taken in past research builds on the joint-occurrence of different technology classes as found in patent documents (Engelsman and Van Raan, 1992; Breschi, Lissoni and Malerba, 2003). Two technology classes are considered as technologically-related if they occur frequently together as technology classification codes on the same patents. In this article, a novel approach, which relies on citation patterns in patent documents, is followed. Two technology classes are considered as technologically-related if patents classified in one technology class often cite patents classified in the other technology class (and visa versa). Since the variation among patent citations is much larger than that of the joint-occurrence of technology classification codes, this approach allows for a more fine-grained characterization of technological-relatedness. Furthermore, arguably patent citations are a more direct measure of technological-relatedness since the cited patents represent 'prior art' relevant to qualify the claims advanced in the citing patent applications. The 'technological universe' on the basis of which our technological-relatedness measure is

calculated is the collection of all EPO patent grants up to 2003 applied for between 1990 and 2003 (and granted before June 2005). Most of these 456,340 EPO patent grants (98%) contain cited patents, which originate mainly from USPTO and EPO[8]. For these citations (969,471) information on technological classes can be extracted and used subsequently to assess technological-relatedness between classes.

A straightforward way to measure the technological-relatedness of two technology classes is to compare the observed numbers of citations between these classes with expected numbers of citations, under the hypothesis of random occurrence of technology classes on cited patents. Let O_{ij} be the observed number of cited patents of technology class j in citing patent grants of technology class i, with $O_i = \sum_j O_{ij}$[9]. A certain technology class has a higher random probability to be cited if many patents are classified in that technology class. Let N_j be the total number of patents that are classified in technology class j, with $T = \sum_j N_j$. This gives the following expression for the expected – random – number of cited patents of technology class j in citing patents of technology class i (E_{ij}):

$$E_{ij} = O_i * (N_j/T)$$

A measure of technological-relatedness is then calculated as follows:

$$R_{ij} = (O_{ij} + O_{jj})/(E_{ij} + E_{ji})$$

This leads to the creation of a 'symmetric' matrix (30x30, with empty diagonal elements) of relatedness measures for each pair of (distinctive) technology classes. The interpretation of R_{ij} is straightforward: if $R_{ij} > 1$, then technologies i and j are more related than could be expected on the basis of random citation patterns. The technology-relatedness matrix is given in Appendix 2.

The technology-relatedness matrix is used to calculate the technological coherence of a firm's technology portfolio, with the latter defined as the weighted (by means of consolidated patent numbers on the level of the firm) average technological-relatedness of all pairs of technologies in a technology portfolio. In line with the work of Teece et al (1994) on product-relatedness measures, our measure of technological coherence at the level of the firm is calculated in two steps. First, for each technology in a firm's patent portfolio, the weighted

average relatedness (COH$_i$) of that technology to all *other* technologies within the firm is calculated:

$$COH_i = (\textstyle\sum_{i \neq j} R_{ij} * P_j) / (\textstyle\sum_{i \neq j} P_j).$$

This measure indicates to which extent technology field i is related to all *other* technology fields in a firm's technology portfolio, weighted by the patent counts in each technology field (P$_j$). The overall coherence measure of a firm's technology portfolio is then defined as the weighted average of all the COH$_i$ measures:

$$COH = (\textstyle\sum_i COH_i * P_i) / (\textstyle\sum_i P_i)$$

The coherence index COH is calculated on the 1-year lagged patent portfolio of the firm, which is taken as a five-year moving window of firms' patent applications. Hypothesis 2 predicts that COH has a positive moderating effect on the impact of DIV on technological performance. Hence, we include the interaction effect of DIV and COH in our empirical analyses and expect a positive sign. The analysis also includes a main effect of COH, to avoid a bias in the estimates of the interaction term between diversification and coherence (Braumoeller, 2004).

Control variables

Our empirical model controls for other factors that are likely to impact technological performance. As emphasized already by Pakes and Griliches (1984), changes in R&D expenditures are likely to result (with small time lags) in subsequent changes in patent numbers[10]. To control for changes in R&D expenditures, the 1-year lagged R&D expenditures of the firm (R&D), measured in constant US dollars (millions) are included. The data on firms' R&D expenditures are collected from annual financial reports (source: Worldscope, Compustat and annual reports). A second control variable is the size of the lagged patent portfolio of the firm (PORTFOLIO). Firms with a large stock of patent applications are expected to be more effective in producing new patent applications. Finally, the model also includes 8 time dummies to account for time-specific factors affecting the number of patent applications.

Descriptive statistics of the dependent and explanatory variables can be found in Table 2. The mean numbers of patent applications and lagged R&D expenditures in our sample amount to 125 and 674 million dollars in respective order. The mean technological diversification measure is 4.56. As one may expect, the patent portfolios exhibit technological coherence: an average value of 1.33 (above 1) for the COH variable indicates that firms combine technologies that cite each other more frequently than a random citation pattern would suggest.

Table 3 contains the coefficients of correlation between the variables of interest. The patent stock correlates highly with the rate of new patent applications. Technological diversification correlates negatively, but not particularly strong, with the level of technological coherence. As to be expected, the correlation between diversification and its squared term is considerable.

INSERT TABLES 2 and 3

Empirical Results

The results of the fixed effects negative binomial estimation of the relationship between technological performance (the number of patent applications, PATENT), technological diversification and coherence are presented in Table 4[11]. Model 1 includes only the control variables. R&D and the size of the lagged patent portfolio have the expected positive signs and are significant[12]. The time dummy coefficients indicate a yearly increase in patent applications up to 2002 (the reference year is 1995), followed by a decline in 2003. The decline in 2003 is partly due to the fact that not all patent applications filed in 2003 had been published and recorded in our database at the moment of data retrieval. In addition, the increasing trend to file patents directly under the PCT Treaty – extending the period between application and publication – explains the observed coefficient.

The linear (DIV) and squared (DIV^2) terms of technological diversification are added in Model 2, showing a positive and significant impact of the linear term and a negative and significant impact of the squared term. These results strongly confirm hypothesis 1: the

marginal effect of technological diversification is initially positive, but decreases after a certain level of diversification to become negative for highly diversified firms. In Model 3, the interaction term between technological diversification and technological coherence, as well as the main effect of coherence, are added. The coefficient of the interaction term is positive and significant while the coefficient of the main effect is negative but not significant. This supports our hypothesis 2: the higher the level of technological coherence of a firm's technology portfolio, the greater the positive impact of technological diversification on a firm's technological performance. Figure 1 illustrates our findings graphically. The figure depicts the predicted values of Model 3, calculated at the sample mean (average values for controls and fixed effect, year dummy 1999 set to 1), for varying values of DIV and COH. Technological diversification varies between 1 and 20 for three different values of coherence: average coherence (COH mean), average coherence minus one standard deviation (COH low), and average coherence plus one standard deviation (COH high). The figures illustrate that the relationship between technological diversification and performance is inverted U-shaped, while higher levels of technological coherence lead to a greater positive impact of diversification on performance. The optimal level of technological diversification depends on the level of technological coherence. For low coherent firms it is around 9, but this value increases to 13 and 16 for mean coherent and high coherent firms, respectively. While one has to be cautious in interpreting the predicted impacts[13], Figure 1 shows that the magnitude of the impact of technological coherence on patent applications is substantial. A high-coherent firm active in 4 equally important (in terms of patent numbers) technology fields is predicted to have 60 percent (123 versus 77) more patent applications than an equally diversified firm characterized by low levels of coherence. Similarly, diversification conditional on sufficient coherence can have a large impact on patent applications. An average coherent firm active in 4 equally important technology fields increases its yearly number of patent applications by 15 percent (97.5 to 115) if it becomes active in a 5th (equally important) technology class.

Conclusion and Discussion

This article examined the relationship between technological diversification and technological performance of firms in conjunction with the technological coherence of firms' technology portfolios. Based on insights from the technology and innovation management literature, technological diversification is expected to have an inverted U-shaped relationship with technological performance. While technological diversification offers opportunities for cross-

fertilization and technology fusion, higher levels of technological diversification may yield fewer marginal benefits as firms risk lacking sufficient levels of scale to benefit sufficiently from wide-ranging technological capabilities. In addition, coordination and integration costs may increase exponentially with higher levels of technological diversification, as highly diversified firms are more likely to encounter difficulties in combining mature (exploitative) technologies with explorative trajectories. Second, the level of technological coherence of firms' technology portfolios is expected to moderate the relationship between technological diversification and performance positively. If firms diversify into 'technologically-related' technologies – i.e. technologies that share a common knowledge base rely upon common scientific principles or have similar heuristics of search – the presence of sufficient levels of scale is ensured while, at the same time, coordination costs may be reduced. Hence, technological coherent diversification puts firms in a better position to increase their technological output. Strong empirical support for our hypotheses is found in a fixed effects panel data analysis of the technological performance (as measured by yearly patent applications) of 184 high R&D spending US, European, and Japanese firms in five high-tech industries.

These findings inform managerial practices with respect to technological diversification in different ways. The study shows that there exist limits with respect to the net benefits of firms' technological diversification, and that too much diversification may negatively impact technological performance. Firms can increase the benefits of diversification and limit the disadvantages by choosing the direction of diversification carefully and extending their activities into technology fields that share a common knowledge base with the firm's existing technology portfolio. So, besides organizational design choices (e.g. O'Reilly and Tushman, 2004), technology characteristics (such as technological-relatedness) should be taken into account when taking strategic decisions on the composition and organization of technology portfolios. The study clearly identifies technological coherence as a promising area for further research. Future research focusing on the adoption of interface management practices directed towards enacting synergies and the precise nature of technological coherence within such processes seems highly relevant. Another avenue for future research relates to analyzing the relationship between technological diversification and firms' financial performance, taking into account the moderating role of technological coherence. The omission of technological

coherence in previous work (Gambardella and Torrisi, 1998; D'Este, 2005; Giuri, Hagedoorn and Mariani, 2004) may be one factor explaining the mixed results of those studies.

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TABLES, FIGURES AND APPENDICES

Table 1: Distribution of sample firms by industry and region of origin

Industry	Europe	Japan	United States
Engineering & General machinery	14	11	11
Pharmaceuticals & Biotech	12	12	14
Chemicals	12	11	11
IT hardware	13	12	17
Electronics & Electrical machinery	12	15	7
Total	**63**	**61**	**60**

Table 2: Descriptive statistics

Variable	Description	Mean	Std. Dev
PATENT	Number of patent applications	125.15	253.07
RD	R&D expenditures	674.54	1070.14
SIZE	Size of patent stock	547.86	1012.03
DIV	Technological diversification	4.56	2.53
COH	Knowledge coherence	1.33	0.95

Table 3: Correlation Matrix

|	PAT	RD	PORTFOLIO	DIV	DIV^2	COH	DIV*COH
PAT	1						
RD	0.722^*	1					
PORTFOLIO	0.926^*	0.754^*	1				
DIV	0.17^*	0.103^*	0.192^*	1			
DIV^2	0.131^*	0.087	0.146^*	0.963^*	1		
COH	-0.138^*	0.008	-0.14^*	-0.338^*	-0.297^*	1	
DIV*COH	-0.018	0.056	-0.002	0.451^*	0.430^*	0.620^*	1

*Note: Significance of correlations is indicated by * (0.01)*

Table 4: Results of Negative Binomial Fixed Effects Panel Data Analysis of Firm Technological Performance (PATENT)

	Model 1	Model 2	Model 3
PORTFOLIO	.1312***	.1193***	.1344***
	(.0211)	(.0189)	(.0198)
R&D	.0934***	.1021***	.0786**
	(.0320)	(.0310)	(.0323)
DIV		.2652***	.1593***
		(.0368)	(.0507)
DIV^2		-.0137***	-.0100***
		(.0029)	(.0030)
COH			-.04725
			(.0824)
DIV*COH			.0740***
			(.0264)
y1996	.1550***	.1301**	.1711***
	(.0579)	(.0555)	(.0561)
y1997	.2134***	.1969***	.2325***
	(.0533)	(.0510)	(.0513)
y1998	.3027***	.2918***	.3267***
	(.0520)	(.0495)	(.0497)
y1999	.3770***	.3709***	.4045***
	(.0507)	(.0483)	(.0483)
y2000	.4557***	.4473***	.4746***
	(.0496)	(.0474)	(.0474)
y2001	.5045***	.4973***	.5177***
	(.0478)	(.0457)	(.0458)
y2002	.5622***	.5619***	.5866***
	(.0462)	(.0441)	(.0443)
y2003	.47685***	.4708***	.4913***
	(.0465)	(.0446)	(.0446)
_cons	1.3012***	.5096***	.6006***
	(.0647)	(.1179)	(.1725)
N	1514	1510	1496
Number of Groups	184	184	184
ll	-5683.998	-5634.725	-5573.248
chi2	376.558	500.8676	478.41

*Note: significance of coefficients is indicated by * (0.1), ** (0.05) and *** (0.01). R&D and portfolio are divided by a factor 1000 in this analysis for reporting issues.*

Figure 1: Predicted Values of Patent Application (PATENT) as a function of Technological Diversification (DIV) and Technological coherence (COH)
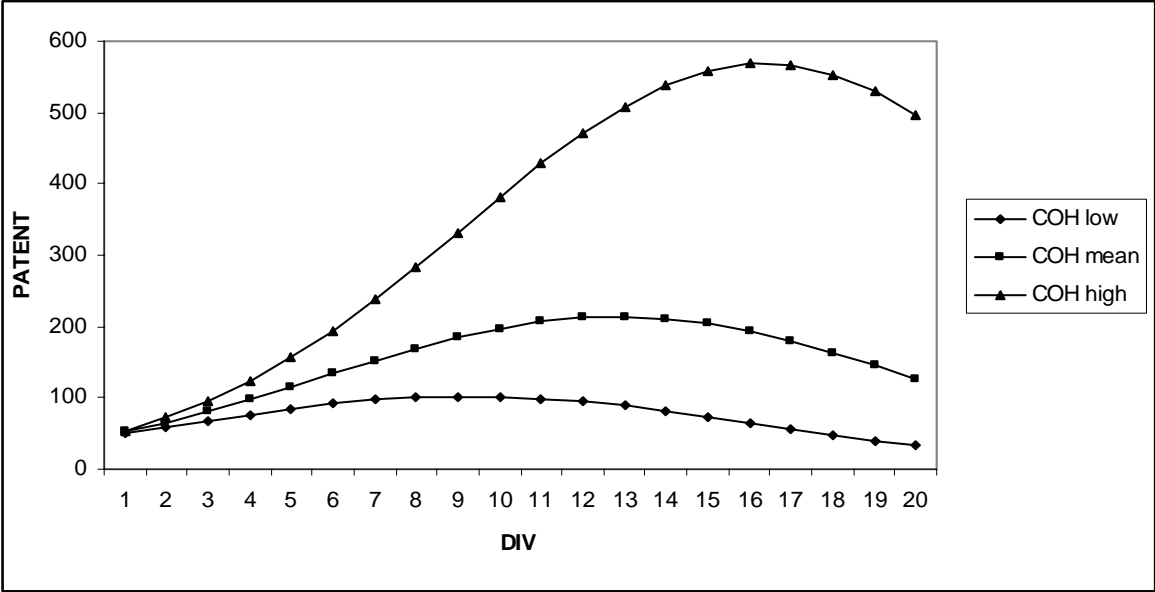
Appendix 1: Technology classification table

1. Electrical machinery
2. Audio-visual technology
3. Telecommunications
4. Information technology
5. Semiconductors
6. Optics
7. Analysis, measurement and control technology
8. Medical technology
9. Nuclear engineering
10. Organic fine chemistry
11. Macromolecular chemistry, polymers
12. Pharmaceuticals, cosmetics
13. Biotechnology
14. Agriculture, food chemistry
15. Chemical and petrol industry, basic materials
16. Chemical engineering
17. Surface technology, coating
18. Materials, metallurgy
19. Materials processing, textiles, paper
20. Handling, printing
21. Agricultural and food processing machinery
22. Environmental technology
23. Machine tools
24. Engines, pumps, turbines
25. Thermal processes and apparatus
26. Mechanical elements
27. Transport
28. Space technology, weapons
29. Consumer goods and equipment
30. Civil engineering, building, mining

Appendix 2: Technology Relatedness Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1																														
2	0.58																													
3	0.50	2.10																												
4	0.35	1.43	2.13																											
5	1.15	0.46	0.35	0.75																										
6	0.55	1.29	0.64	0.36	1.04																									
7	0.60	0.49	0.84	1.39	0.47	0.50																								
8	0.14	0.13	0.06	0.22	0.05	0.25	0.52																							
9	1.12	0.44	0.23	0.34	0.84	0.74	0.98	1.10																						
10	0.04	0.05	0.00	0.01	0.03	0.36	0.29	0.07	0.03																					
11	0.33	0.18	0.01	0.01	0.20	0.90	0.07	0.51	0.05	1.14																				
12	0.01	0.01	0.00	0.01	0.01	0.04	0.27	0.74	0.08	4.86	0.65																			
13	0.01	0.01	0.01	0.03	0.02	0.04	1.68	0.30	0.07	2.44	0.27	2.56																		
14	0.07	0.00	0.00	0.01	0.01	0.01	0.08	0.19	0.02	0.68	0.46	1.86	3.26																	
15	0.17	0.16	0.00	0.01	0.15	0.71	0.12	0.26	0.73	2.77	2.07	1.18	0.91	1.19																
16	0.23	0.06	0.02	0.11	0.28	0.16	0.74	0.57	0.59	1.41	0.88	0.40	0.67	0.93	1.70															
17	0.91	0.45	0.04	0.06	1.67	0.73	0.19	0.57	0.94	0.14	1.98	0.08	0.07	0.19	0.70	1.08														
18	0.90	0.13	0.03	0.01	0.88	0.45	0.13	0.17	1.28	0.34	0.96	0.21	0.07	0.14	1.21	2.18	2.41													
19	0.30	0.22	0.02	0.08	0.14	0.49	0.21	0.59	0.15	0.18	2.69	0.16	0.13	0.29	1.05	1.02	2.61	1.00												
20	0.24	0.31	0.14	0.32	0.21	0.74	0.70	0.38	0.16	0.05	0.43	0.05	0.05	0.43	0.21	0.72	1.19	0.15	1.07											
21	0.10	0.05	0.03	0.07	0.02	0.02	0.31	0.24	0.02	0.05	0.17	0.14	0.32	4.40	0.43	0.72	0.29	0.07	0.34	0.54										
22	0.18	0.02	0.01	0.01	0.04	0.08	0.22	0.26	1.05	0.30	0.44	0.10	0.59	0.48	1.31	6.41	0.82	2.78	0.48	0.12	0.39									
23	0.47	0.07	0.03	0.11	0.54	0.28	0.37	0.27	0.86	0.02	0.14	0.02	0.01	0.12	0.25	0.44	1.08	1.30	1.01	0.80	0.53	0.33								
24	0.46	0.02	0.05	0.07	0.11	0.02	0.51	0.21	0.16	0.01	0.02	0.00	0.00	0.02	0.08	0.55	0.34	0.42	0.11	0.13	0.09	2.14	0.45							
25	0.73	0.03	0.04	0.06	0.34	0.10	0.51	0.16	0.60	0.02	0.06	0.01	0.05	0.39	0.46	1.38	0.41	1.83	0.35	0.19	0.52	2.89	0.75	1.76						
26	0.44	0.10	0.04	0.07	0.08	0.08	0.41	0.31	0.23	0.01	0.13	0.00	0.01	0.03	0.08	0.31	0.51	0.30	0.58	0.47	0.37	0.44	0.99	1.74	0.63					
27	0.52	0.10	0.17	0.19	0.05	0.13	0.53	0.09	0.05	0.01	0.23	0.00	0.00	0.01	0.04	0.11	0.33	0.13	0.44	0.33	0.29	0.29	0.30	0.86	0.59	2.65				
28	0.22	0.11	0.28	0.17	0.19	0.35	0.87	0.05	0.13	0.05	0.14	0.03	0.03	0.03	0.12	0.23	0.60	0.45	0.20	0.18	0.13	0.19	0.19	0.35	0.34	0.31	1.12			
29	0.27	0.36	0.09	0.28	0.23	0.19	0.37	0.71	0.10	0.01	0.22	0.06	0.02	0.37	0.10	0.40	0.86	0.12	0.72	0.77	0.50	0.22	0.73	0.13	0.92	0.55	0.58	0.43		
30	0.23	0.10	0.12	0.09	0.05	0.08	0.36	0.06	0.17	0.02	0.21	0.01	0.03	0.02	0.27	0.35	0.65	0.50	0.40	0.29	0.53	0.61	0.61	0.26	0.46	1.40	0.78	0.43	0.68	

ENDNOTES

[1] An exception is Nesta and Saviotti (2005) who examine technological diversification and coherence of patent portfolios for a small sample of US bio-pharmaceutical firms. They use a coherence measure due to Breschi, Lissoni and Malerba (2003) and find that coherence has a positive impact on a firm's number of biotech patent applications.

[2] Prencipe (2004) provides evidence for the absorptive capacity argument. For three leading firms in the aircraft engine industry, he noted that their internal technology portfolio remained very broad over time, despite an increase in the outsourcing of the development of components to suppliers.

[3] Suzuki & Kodama (2004) found empirical proof of such intra-firm cross-fertilization dynamics when analyzing the inventive activities of two large Japanese firms, Canon and Takeda. Canon benefited from the knowledge of camera technologies to develop the technological trajectories of both copiers and semiconductor manufacturing equipment, while knowledge in the field of 'microbes and fermentation' enabled Takeda to deepen competencies in 'organic chemistry'.

[4] See, for instance, the development of a first affordable computerized numerical controller for industrial machine tools by Fanuc as documented by Kodama (1992).

[5] These studies examined patent application data of 31 US bio-pharmaceutical firms, and 544 EU firms (from different sectors), respectively.

[6] For the distinction between exploration and exploitation we refer to March (1991).

[7] We selected industries with the highest patent propensities as reported by Arundel and Kabla (1998): Pharmaceuticals (74%), Chemicals (57%), Machinery (54%), Precision instruments (53%), Electrical equipment (43%) and IT Equipment (36.5%).

[8] For citations to patents granted by patent authorities other than EPO and USPTO (about 40 percent of citations), no technology class information was available on a systematic basis. We have worked thus exclusively with EPO and USPTO cited patents found in EPO patent grants.

[9] We make no specific assumption about the form of the distribution of technology classes across cited patents

[10] Pakes and Griliches (1987) show that the relationship between R&D expenditures and patents is especially strong at the cross-sectional level (R-squares of 0.9), while the same relationship is also significant (but weaker) in the within-firms time-series dimension (R-squares of 0.3)

[11] We executed a Hausman test which compares random effects and fixed effects estimations of the model. This test rejected the appropriateness of using random effects estimation.

[12] Conservative 2-tailed tests are being used throughout.

[13] We note that parts of the graphs fall out of our sample range: the maximum sample values for DIV are 15, 8 and 5.5 for low, mean and high coherent firms, respectively. In addition the predictions are conditional on taking all other covariates in the sample mean.