Innovation Leadership, Technological Coherence and Economic Performance

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Abstract

The central research question in this paper is: what is the relationship between the economic performance of the firm and (i) strategies of being a technological leader versus a technological follower, and (ii) strategies of established technological coherence versus novelty in technological combination? We present a quantitative investigation that enables us to formulate some empirically grounded generalizations of average tendencies across firms with different technological strategies in a specific industry, the biotechnology industry. Our results suggest a bifurcation in the structure of corporate innovation strategies with respect to both leadership and coherence.

Keywords: Innovation leadership; Technological coherence; Absorptive capacity; Economic performance.

JEL-classifications: O31, O32, L20, L65.

1. Introduction

In this paper, we examine how leadership in technological innovation and the degree of coherence in profiles of technological capabilities are related to corporate economic performance. We focus upon how the ability of firms to realize increased economic value through innovation relates to corporate technological strategies in terms of whether a firm is a leader or a follower, and in terms of whether it is more oriented to coherent or to experimental combinations of activity. These are both issues that have been centrally raised in the work of David Teece (Teece, 1986; Teece et al., 1994). We illustrate our argument with reference to empirical evidence from the biotechnology industry, and examine these questions through the lens of the competence-based theory of the firm.

In the traditional market-based general equilibrium framework, firms profit from innovation by obtaining first mover advantage, through earning the rents associated with positions of (temporary) market power. This interpretation, while fitting well with the market structure framework in which the firm is primarily perceived as a price and output decision-maker, loses the distinctiveness of Schumpeter's (1943) notion of innovation as a disequilibrium process in which firms profit from innovation by adding new elements of value creation that expand the existing circular flow of income (Cantwell, 2002). As suggested by Schumpeter, innovation brings in the most sustainable long term corporate profits by facilitating an ongoing stream of long-term profit creation through the continued expansion in the scope of the value creating activities of the firm. In this perspective, it is more appropriate to view innovation as a problem-solving search that creates and continually renews technological or social capability within firms, and not as a search for positions of market power as such.

The introduction of a resource-based view of the firm by Penrose (1959), who defined the firm as a pool of resources, has since given rise to a competence-based theory of the firm, in which the firm is an agent that creates and sustains dynamic capabilities. In the competence-based approach, the firm is understood in part as a bundle of technological capabilities, as a locus for learning and problem-solving efforts, and as a qualitative dynamic coordination mechanism that aligns the creation, acquisition, and coordination of relevant knowledge (Loasby, 1999). In this event, the major issue in the ability of firms to profit from innovation (or from positions of leadership in innovation) is not so much how well firms exploit some specific new technology when considered in isolation, but is rather how smooth is a firm's internal creative process (although it often draws upon cooperation with other firms or organizations) in adapting and extending its knowledge base, or more especially, its technological capabilities. This approach thus immediately renders as crucial the linkage between own-capabilities and what has become known as the absorptive capacity (Cohen and Levinthal, 1990) to recognize and assimilate the knowledge of others, which connects in-house research and development (R&D) and learning with the scope for inter-firm exchanges in innovation.

As theoretical and empirical studies have shown, technological leaders are not necessarily the firms that are most profitable. Some may even fail in competition with followers in their market (Teece, 1986; Cantwell and Andersen, 1996). The varying relative fortunes of followers-imitators versus leaders-innovators in different industries and at different times can be explained in large part by the crucial role of complementary capabilities. To obtain a certain technology, a firm can either develop it by relying essentially just on its own efforts through in-house R&D, or it can develop the absorptive capacity needed to acquire it externally from others and to adapt it so as to be able to integrate the technology with its internal capabilities. Thus, complementarity can be considered in two respects. Internally complementary capabilities support the success of in-house innovation and allow the firm to profit from its leadership in innovation. Teece (1986) has argued that certain co-specialized assets are necessary for successfully commercializing an innovation. Followers that are better equipped with the crucial complementary assets may obtain most of the profits from innovating, while the leader may die if it lacks such complementary assets. The ability to establish and maintain leadership thus depends on the overall technological complementarity of the profile of assets held by the firm. Even when the firm acts as a follower, its ability to evaluate and utilize external knowledge is also a function of the preexisting knowledge base of the firm, or its "absorptive capacity" as defined by Cohen and Levinthal (1990). In her theory of the growth of the firm, Penrose had emphasized that the boundaries of growth are set by the technological base of the firm. The direction of corporate learning and growth, she argued, is a path-dependent and resource-constrained process.

What is more, increasing technological complexity further blurs any distinction between innovation and imitation (Cantwell, 2002). Imitation requires the related absorptive capacity that comes from innovation, while innovation always incorporates some elements of imitation. Thus, in the analysis of relative technological positions (as opposed to the speed of market entry), the distinction between either leading or following in innovation is a matter of degree rather than kind, and involves the relative balance between innovation and imitation. Leaders have a balance that is more tilted towards innovation, while followers have a balance tilted more towards imitation. The intertwining between innovation and imitation indicates that leading or following in innovation, the extent of coherence or experimentation in the creation of complementary capabilities, and the related absorptive capacity all influence how the firm can profit from innovation. The firm may profit as an innovative leader by maintaining a sufficient coherence in its profile of complementary assets, or as a follower especially when this strategy is supported by a strong absorptive capacity.

We use the biotechnology industry to study how the firm's role as a leader and its parallel role as a follower influence its economic performance. Following Cantwell and Andersen (1996), we define the technological leadership as specialization by a firm relative to others in its industry, in the fastest growing fields of activity amongst those that are most relevant to technological development in that industry. Each firm's pattern of technological specialization is measured by an index termed as revealed technological advantage (*RTA*). We measure the degree to which each firm's internal capabilities are complementary according to the established standards of the industry by the overall coherence (or goodness of fit) of its corporate technological profile with the wider industry pattern of cross-field connections. We calculated the firm's absorptive capacity in the fastest growing fields by the extent to which it is specialized in activities that are well related to these fields (using the measure of technological relatedness between fields proposed by Teece et al., 1994). This index is intended to capture the complementarity that confers a higher absorptive capacity that enables both leaders and followers to execute their respective strategies more effectively. The sample we use in the study includes all the companies that appeared in *NASDAQ* Biotechnology 100 Index during 2000-2004 (which are the years available) and companies listed in the *NYSE* in 2004.

Our study discusses only innovation and capabilities in technology, and thereby neglects any explicit treatment of other connected functions (i.e. organization, marketing) that are important. However, when the economic history of the past 100 years is viewed as a whole, technological innovation is increasingly becoming the central organizing principle. The steadily rising significance of innovative profits relative to the more traditional kind of profits derived from the exercise of market power in a market for an established product with a stable process of production, justifies our focus on this aspect of capabilities. Also, R&D activities are the most prominent driver of the growth in the biotechnology industry (US Department of Commerce, 2004). This new-born, fast growing and science-based industry is a good candidate to study and test the cross-firm evolution of technological activities.

Our central research question is: what is the relationship between the economic performance of the firm and (i) strategies of being a technological leader versus a technological follower, and (ii) strategies of established technological coherence versus novelty in technological combinations? In answering this question, the paper provides three main contributions to the literature on the competence-based theory of the firm. First, most existing studies of the relative success of innovators-leaders versus followers-imitators have either been essentially theoretical (usually based upon simulation exercises), or they have used qualitative case study approaches. In this paper we present a quantitative investigation that offers greater scope for empirically grounded generalizations of average tendencies across firms with differing strategies in an industry. Second, the paper combines innovation leadership, overall corporate technological coherence, and absorptive capacity in relating economic performance to technological innovation, and we thereby incorporate dynamic interaction effects between these factors in the processes of learning and innovating in the firm. Third, we apply the relatedness measure of Teece et al. (1994) to an analysis of the effect of overall corporate technological coherence (in addition to absorptive capacity) within a firm. In particular, we are thereby able to distinguish between strategies of established technological coherence that best exploit existing capabilities, as against strategies of experimenting with a greater novelty of technological combinations that shift the balance of learning towards more exploration in the boundaries of corporate technological search (to adapt the terminology of March, 1991).

In the next section, we first elaborate upon the conceptual framework for the study and propose how economic performance may be related with innovation leadership, corporate technological coherence, and absorptive capacity. A description of the data and sample selected appear in section 3, while the methodology and models follow in section 4. We then present the empirical results in section 5. A discussion of the findings concludes.

2. Innovation leadership, technological capabilities and profits

Following Schumpeter (1943), we can distinguish between two means for creating profits: profiting from market power in static market structures characterized by imperfect competition, and profiting from innovation through creating new sources of value added associated with some distinctive technological and organizational path for learning. While the first realm is consistent with the traditional general equilibrium analysis, which treats firms as homogeneous units in the process of economic exchange that decide prices and quantities in the relevant market(s), firms in the second realm are reservoirs of technological capabilities and devices for learning and development based on dynamic capabilities. Innovation, which is an empirically exploratative (generally non-deductive) and open-end novelty-creating economic activity, is more institutionally embedded in and reliant upon a complex network of external knowledge connections and a flexible profile of internal knowledge capabilities entailing knowledge transfers between firms, and between firms and other organizations.

Following the classical tradition, Schumpeter was concerned with the problem of economic development – of the creation of wealth – rather than with questions of the simple allocation of resources (Langlois, 2002). In Schumpeter's view, competition from imitators following innovations gradually reduces the profits from innovation at an industry level. His theory stresses solely the need to identify the original sources of innovation as opposed to subsequent imitation in order to explain the tendency within markets for innovative profits to be subsequently whittled away through technological competition. Therefore, his approach was not concerned with the extent to which imitators might also share in the distribution of profits from innovation. He did not consider at all the still more fundamental challenge that imitators (since they also have some mix of innovation and imitation) may themselves also be the origin of new sources of value added, and hence of innovative profits.

Cantwell and Andersen (1996) show that although amongst large firms technological leaders tend to retain a leadership position from one phase of development to another, the fields in which other firms catch up faster exhibit the highest level of the industry innovative profits and technology-based growth. This suggests that innovative profits are created not just by "leaders" but also by "followers". It will not necessarily be leaders that earn the highest rewards from innovation and hence enjoy the fastest growth, and the existing historical evidence does indeed suggest that while sometimes leaders have an advantage in subsequent performance, sometimes followers have the competitive edge (Teece, 1992; Andersen and Cantwell, 1999). If innovation is profitable at the very beginning, followers may only grab a smaller share of profits compared to leaders. However, when innovation is risky and costly and when external inter-firm learning is high relative to internal intra-firm learning, first movers in the innovation may be at a disadvantage, while the followers may learn from the mistakes of leaders and earn larger profits (Silverberg et al., 1988).

In this respect, the sharpness of Schumpeter's distinction between entrepreneurial innovator-leaders and follower-imitators may be unhelpful. Although social capability is created through internal learning processes within firms such learning is interactive and involves continuous exchanges of knowledge, whether through deliberate cooperation in learning or independent exchanges through licensing, imitation or the like (Cantwell and Barrera, 1998). Defining innovation to be what is new to a firm with its own differentiated area of expertise or what is new to a particular local context rather than as something new to the world as a whole (Nelson, 1993), the most effective corporate innovators are not necessarily the technological leaders whose expertise is focused on the leading edge fields as such. They may be other firms that have found the most productive industrial applications of the leading edge technologies, which applications themselves require further innovation and other supporting capabilities - linked in part to the process of critical revision of new technologies which enhances their workability and effectiveness, as emphasized by Usher (1954) and Rosenberg (1982).

The blurring of the boundary between innovators and imitators is entirely intelligible in terms of the most recent literature on the evolutionary approach to technological change which has stemmed from the work of Nelson and Winter (1982) and Rosenberg (1982), and in the process rediscovered the contribution of Penrose (1959). In the evolutionary theory of technological change innovation is always context-specific and localized since learning builds incrementally through guided experimentation on what is already known, and so capabilities – including the capabilities to envisage new productive opportunities – are always context-specific.

Lee and Harrison (2002) show by developing a dynamic model with adaptive and experimental learning that it is plausible for two bifurcating strategic groups to emerge in an innovating industry, which two alternative corporate strategies are defined by a polarization across firms in their respective choices of the allocation of resources between two R&D options – innovation and imitation. The critical firm strategic decision in this respect involves the allocation of R&D investment between leading in innovation or following, and according to this argument to be successful the firm needs to demonstrate clear consistency in its chosen strategy, because of the highly uncertain nature of R&D activities which confer high potential returns but also high risk. The least effective "strategy" is thus being stuck in the middle, neither consistently leading nor consistently following, and thus without a clear corporate innovative strategy. Crucial to the bipolarization of firm strategies in the Lee and Harrison argument is that when firms incrementally adapt their capabilities (as they do, according to the evolutionary approach summarized earlier), incumbent firms will tend to become locked into a development path in which R&D resources are either committed more to innovation (amongst those that become the most successful innovators from the outset), or alternatively more to imitation (amongst those whose initial innovations perform less well or fail).

The capabilities, organizational routines and search procedures that are required for a strategy of leading in innovation and a strategy of following may be different. If the capabilities and procedures for learning required are sufficiently distinct, then given that resources for growth and development are limited (as stressed originally by Penrose), firms may well have to make a clear strategic choice between these two alternative strategies. Trying to maintain a foot in both camps risks doing neither well, once we recognize that there is some element of trade off between innovating in a leading edge area and innovating more in the applications of leading edge developments through fusing them with technologies in other related fields. In this case two distinct strategies for innovative profit creation may emerge, such that the relationship between technological leadership and economic performance becomes U-shaped.

Hypothesis 1: Both firms with high leadership in innovation and firms with low leadership (i.e. followers) tend to perform better than firms that are neither leaders nor followers.

In his seminal contribution, Schumpeter (1934) defined innovations as "new combinations" of productive means that entail some element of discontinuity from the past. In building upon this conceptualization of innovation, we can recognize that such new combinations may entail differing extents of discontinuity from the technological and associated organizational methods of the recent past. On the side of lesser discontinuity from the past, one strategy for firms is to focus their learning on intensively exploiting an established relatedness between two fields of technological activity, to develop new combinations that adapt the existing strengths of the firm in spanning these two fields of endeavor. On the side of greater discontinuity or challenge, an alternative strategy for firms is to experiment with potential new combinations of fields that have as yet been relatively unexplored, and so between which fields no relatedness has thus far been established. This too suggests a possible bifurcation of corporate strategies, between a strategy of learning in and around combinations that are known to be coherent, as opposed to an experimental strategy of attempting to establish more thoroughly novel combinations of technology.

Thus, the extent of corporate technological coherence reflects a further aspect of a firm's innovation strategy. The degree of corporate technological coherence exhibited by each firm's profile of activity represents the overall complementarity of the firm's technological capabilities, which composition is the outcome of a process of learning and accumulation through the firm's internal technological activities. Firms internally develop their competence in two dimensions: deepening, by exploiting established strengths more thoroughly, and widening, by exploring novel combinations that expand upon existing strengths (March, 1991; Breschi et al., 2000; Cantwell and Mudambi, 2005). A deepening pattern of innovative activities involves the continuous consolidation of a closely related technological profile of activities that have been accumulated through the highly focused exploitation of existing technological capabilities. A widening pattern of innovative activities, in comparison, involves a continuing enlargement of the technological base through exploring novel potential combinations that incorporate developments from new technological fields. Especially in an R&D-intensive industry, firms are confronted with a strategic decision between two options on R&D investment: exploiting more intensively an expertise in currently established combinations of technologies, or exploring new forms of more experimental technological combination.

On the one hand, for relatively stable technology fields, like those of the old pharmaceutical industry, the direction of technological advancement may become reasonably well defined, such that we can expect a convergence of firms around a primary or dominant strategy of a clear focus on a consistently coherent path in continuing technological exploitation and absorption based on their existing technological profiles (Cohen and Levinthal, 1990). As shown in previous literature, the world's largest firms tend to display coherence in their patterns of corporate technological diversification (Pavitt et al., 1989; Granstrand and Sjölander, 1990; Grandstrand et al., 1997).

However, on the other hand, matters may be quite different in technology areas that are experiencing unexpected turbulence (Bosch et al., 1999), like the "therapeutic revolution" spurred by the discovery of rDNA technology in the pharmaceutical and biotechnology industry. The rise of a new, complex technology system may require an industry group to shift the balance in its technological learning towards greater exploration, which involves introducing new technological fields and deriving novel distinct combinations of existing capabilities. In this event, in terms of the evolution in the structure of the industry's population of firms, while one group of firms may continue to emphasize technological coherence, a second strategic grouping may emerge that emphasizes instead a greater element of experimentation or exploration in technological combinations. The efficiency of relying on the relatedness of the current technological base may not be the only viable strategy in a turbulent technology environment, such as that characterized by the newly emergent biotechnology industry. Exploiting technology only in those areas that lie closest to its existing expertise may cause the firm to fail to catch on to radical shifts in the industry, or to miss other potential windows of opportunity (Zahra and George, 2002). Research in the area of cognitive and behavioral sciences suggests that diversity enhances a firm's learning and innovation abilities in two ways: through the experiences gained by learning dissimilar knowledge, and through the creation of novel associations with and linkages to existing knowledge (Cohen and Levinthal, 1990).

Thus, in a turbulent knowledge environment, at least some firms are likely to make greater efforts to increase the scope and the extent of flexibility in the dimensions of their technological capabilities, which being experimental may not conform to the norms of coherence as established from the recent history of the industry, but which novelty makes these firms more potentially adaptable to a changing environment, and enhances the likelihood of their generating new and unexpected combinations from their existing capabilities. Yet here too the capabilities, organizational routines and search procedures that are required may be different for a strategy of further exploiting established technological coherence, as opposed to a strategy of experimenting with more exploratative new combinations of technological effort. In other words, we might again expect that two distinct strategies for innovative profit creation may emerge, where in this case the relationship between established technological coherence and economic performance becomes U-shaped.

Hypothesis 2: Firms with either highly coherent or highly experimental combinations of technological capabilities are likely to perform better than the firms with neither coherent nor experimental combinations of capabilities.

Technological change is always context-specific and localized (Nelson and Winter, 1982). A technology developed in one context requires the cost of further innovation to be transferred into some other (Teece, 1977), but the cost or difficulty of subsequent innovation depends upon the initial degree of technological relatedness or complementarity between the combination of activities in the originating and in the recipient contexts (Cantwell and Barrera, 1998), and upon the degree of absorptive capacity in the recipient or imitating firm (Cohen and Levinthal, 1990). When firms have a higher degree of technological complementarity between their profiles of specialization and the external innovation, they will have a greater absorptive capacity with respect to being able to take advantage of the knowledge being created by others. In systemic networks of inter-company interaction in innovation the greatest profits are likely to accrue to firms that have the best fit between their initial capabilities and the fields of the greatest new opportunity, as opposed to firms that are the first to initiate a new line of innovation. The greatest benefits do not necessarily go to the "first to discover" or the "first to commercialize" a core technology with important implications. Instead, the greatest innovative profits may rather accrue to firms whose social capabilities are best adapted to absorb, and to further develop and entrepreneurially to apply, the new lines of innovation that have emerged from the fields of greatest technological opportunity to novel contexts, and in new combinations with other branches of (and perhaps with more traditional fields of) technology.

Absorptive capacity matters for all the strategic groups identified earlier, although for somewhat different reasons. For leaders focused on the fastest growing fields absorptive capacity is needed to obtain knowledge spillovers from other leaders with a related focus, and from followers developing applications that lead to a search for adaptation that feeds back into efforts in the fastest growing fields themselves. Followers are characterized by a relatively greater need for imitation, so they need especially a capacity to absorb the pioneering achievements of leaders in the fast growing fields.

Coherent firms need absorptive capacity for those of the fast growing fields that are most related to the structure of coherence on which they rely. More experimental firms need absorptive capacity in the fast growing fields that are most related to the particular new combinations that they are exploring. In general, all firms need absorptive capacity since they all have some mix of innovation and imitation (as argued earlier), and the ease of imitation always depends upon the extent of absorptive capacity.

Hypothesis 3: Absorptive capacity related to the fastest growing fields of innovation for their industry is critical for firms to profit from innovation. Firms with the highest absorptive capacity for the fields of the fastest growing new technologies that are relevant to their own existing capabilities are more likely to be able to achieve economic gains from their innovations.

3. Data and Sample

3.1 Patents as an indicator of technological capabilities

Different indicators have been applied in studying the technological activities of firms. Disaggregated R&D information is rarely available at the firm level, and when it is, it is generally broken down by corporate division rather than by the type of activity. Some researchers use innovation survey data, which is hard to generalize or again to categorize into detailed fields of corporate specialization. These weaknesses of R&D and innovation survey data explain the relative success of patents as an indicator of the distribution of innovation activities across and within firms, in comparative context. The United States Patent and Trademark Office (*USPTO*) keeps records of patents granted since 1790. More important, *USPTO* provides a consistent technology classification for each patent granted. The completeness, continuity, and consistency of the patent data provide us with a good indicator of corporate technological capabilities, especially for larger firms, and especially in science-based industries.

However, there are some potential problems in using patents. Technologies from different disciplines may be closely integrated. And arbitrariness cannot be avoided in the division between certain patent classes (Cantwell, 2004). Even without the problems in patent classifications, it is necessary to recognize that patents have limited use among smaller firms outside the science-based industries. Moreover, the codified knowledge embodied in patents usually cannot be readily translated into production and commercialization, but are rather indicative of knowledge inputs that are needed in the processes of learning which generate the tacit capabilities of firms, and which knowledge can only be used effectively in combination with such capabilities.

We rely on the methodology of Cantwell (2004) to alleviate the difficulties in directly using the patent classification system by regrouping the 401 patent classes of the *USPTO* classification system into 56 technology fields. Since we are studying a single industry here, we further divide the Biotechnology and Pharmaceutical field into 4 subfields. Each patent is assigned to a technological field. Some technology fields do not appear among firms of the biotechnology industry. To alleviate the small number problem in using patent data, instead of studying distributions of activity across all 56 technological fields, we only study the 25 most active technological fields, which have accumulated over 100 patents applications by our selection of firms in the US biotechnology industry between 1985 and 2004.

3.2 The sample

The sample includes all the companies that appeared in *NASDAQ* Biotechnology 100 Index during 2000-2004 (which is the period available) and companies listed in the *NYSE* in 2004. The initial sample includes 230 public biotechnology and pharmaceutical companies (including foreign companies). After excluding companies that do not have any patents, the final sample consisted of 202 companies.

We treat the 202 companies as a representative sample for the U.S. biotechnology industry[1] and use their patenting activities between 1985-2004 to calculate industry reference points, including the patent growth rate of each technology field (to ascertain which are the fastest growing fields for the industry as a whole), and the extent of technological relatedness between any two fields.

Furthermore, we study corporate economic performance in three periods: 1990-1994, 1995-1999, and 2000-2004. The patenting activity of firms during each of these periods is used to depict the composition of their firm level technological characteristics at the equivalent times. We study the economic performance only of firms that meet the following requirements: (1) Only firms incorporated after 1976 are included. Owing to this time constraint, we concentrate on newly established biotechnology firms. The first US firm to exploit rDNA, Genentech, was established in 1976. Older firms, such as traditional pharmaceutical firms, are also doing R&D in biotechnology. However, both their knowledge bases and their market characteristics are quite different from those of the new biotechnology firms. (2) We also suspect that very new firms will be different (subject to a much higher variance in performance), and they may well present measurement problems due to insufficient numbers of accumulated patents. For example, it may be inappropriate

[1] According to Ernst & Young's 2004 biotechnology industry report, there are 1,473 biotechnology companies in the United States, of which 314 are publicly held. It is reasonable to believe that the sample is well defined and representative of the U.S. biotech industry.

to study the technological capabilities of a one-year-old company by the patents for which it has applied so far. Thus, we relied on the criterion of having a minimum of 5 years in operation to select companies for this performance study. That is, companies in the 1999 sample should have been incorporated in or before 1994. (3) Firms needed to have applied for patents in more than one field during the relevant sample sub-period. (4) We needed firms for which financial data, including annual stock prices and total sales were available from *Computstat* or *Mergent*. Selecting in accordance with these criteria, we have 17 companies for 1990-1994, 55 for 1995-1999, and 83 for 2000-2004. Because of the administrative time lag between patent application and patent grant, we have been cautious and so included a dummy variable for the 2000-2004 period.

3.3 Data

We used *Delphion* to collect patent data, including the patent number, the date of granting, the date of filing, and the current U.S. classification for each patent. There are two types of classifications for US patents: the US classification and an International Patent Classification. We used the US classification in the study because it better reflects the technological content of patents. The patent portfolio of each firm has been consolidated by corporate group, such that it includes all patents assigned to itself and to all of its subsidiaries during a sample period. We used *Mergent* and *SEC* filings to identify companies' subsidiary structure in each subperiod. The total revenues and R&D expenditure were manually collected through online editions of *Mergent*. Stock prices were taken from *Compustat* through *WRDS*.

4. Model and methodology

4.1 Dependent variable: economic performance as measured by the annual growth rate of stock prices

Since most biotech firms have been incurring accounting losses, earnings per share or any other index for economic performance related to net income may not be meaningful here. Also, in this industry the value of firms is essentially the value of the technological assets they generate and investment money was raised on the basis of promise in the future. An index for each firm's long run economic performance is thus more appropriate here. Research in finance has shown that the stock price tends to be closely correlated with future earnings. In our sample, technological performance as measured by the annual growth rate of patents of biotech firms shows a positive and significant relationship with the growth in their annual stock price. We thus use the average annual growth rate of the stock price during each sub period as an indicator of the firm's economic performance.

The time spans involved here were 5 years, and observations were recorded annually within these periods. Assuming that the "true" growth during a period was uniform and exponential but each observation was subject to multiplicative error, we use the following regression fit to a uniform growth model (Rumelt, 1974) to estimate the annual growth rate of the firm's stock prices:

$$\tilde{S}_t = Ae^{gt}\tilde{g}, \quad \text{for } t = 1, 2, 3, 4, 5.$$

where $\tilde{S}_t$ is the observed annual average stock price, g is the 'true' uniform growth rate to be estimated, $\tilde{g}$ is a random error term with a mean of one, and A is a constant. Taking the logarithms of the above equation we have

$$\log \tilde{S}_t = \log A + gt + \tilde{e}, \quad \text{for } t = 1, 2, 3, 4, 5.$$

where $\tilde{e}$ is the now additive error with a zero mean.

4.2 Independent variable: technological leadership

As in Cantwell and Andersen (1996), we define the technological leadership as specialization by a firm relative to others in its industry, in the fastest growing fields of activity amongst those that are most relevant to technological development in that industry. In the way in which corporate technological leadership has been defined here, smaller firms may be leaders if they are particularly oriented towards development in the fastest growing areas, although the absolute level of their activity in these fields may be less than that of giant companies which specialize instead in mature technologies and so act as followers. Hence, giant corporations may be either technological leaders or followers; what matters is neither their overall size nor their overall degree of specialization, but rather the actual composition or profile of that specialization – that is, whether their resources are especially geared towards development in the fastest growing fields.

As a leader, a firm is particularly specialized in the fastest growing areas which have the greatest impact on the biotechnology industry. Our first objective is then to identify the fastest growing technological fields. We compare the number of patents in each field applied by the firms during two periods: 1985-1992 and 1993-2000.[2] The growth rate of patents in Field i is measured as follows

$$GrowthRate_i = \frac{P_{i2} - P_{i1}}{(P_{i1} + 1000)}$$

where P_{i1} is the number of patents applied by all firms in Field i during 1985-1992 and P_{i2} is the number of patents applied by all firms in that field during 1993-2000. Adding 1,000

[2] We include only the patents that were applied for before 2000, considering the time lag between application and assignment of patents.

in the denominator avoids the exaggeration in the growth rate that would otherwise be caused by having a small number of patents during the first period.

[Table 1 here]

For the purposes of identifying the structure of corporate technological leadership in the biotechnology industry, we rank the growth rates of patenting in the 25 fields as shown in Table 1. The "leadership" of a firm is measured by the distribution of its patenting activity across fields, relative to its rivals in the same industry. Each firm's pattern of technological specialization is measured by an index termed as revealed technological advantage (*RTA*). This index measures the concentration of the firm's technological specialization in favored fields. The *RTA* for each firm's particular technical field is defined by the firm's patent share of *US* patents applied for[3] in that field by all firms, relative to the firm's overall share of all *US* patents applied for by all the firms in the industry. Specifically, denoting as P_{ij} the number of *US* patents applied in field i by firm j in a particular industry, the *RTA* index is defined as follows:

$$RTA_{ij} = \frac{P_{ij} / \sum_j P_{ij}}{\sum_i P_{ij} / \sum_i \sum_j P_{ij}}$$

Cantwell and Andersen (1996) point out that the reliability of the *RTA* index may be harmed by small numbers of patents in total in certain categories. Regrouping patents into the 25 most important fields is one of the ways to solve this problem.

*RTA*s reflect how the firm allocates its technological activities among the fields with the greatest growing opportunities. Here we are interested in how the firm's *RTA*

[3] In distinction from Cantwell and Piscitello (2000), we establish the firm's patent portfolio according to the patent's application date, instead of the date of granting. For example, for a firm's patent portfolio in year 2000, we include all subsequently granted patents that were applied for before January 1, 2001.

distribution across the 25 fields matches with the industry growth rates of these fields. The more the firm's *RTA* distribution matches with the industry growth rate of the 25 active fields, the more of the firm's resources are oriented towards the fields with the greatest opportunities, and the higher the firm's leadership ranking in innovation. The leadership of firm j is measured by the coefficient of correlation b_j in the following regression. b_j measures the match between the firm's specialization and the industry-wide fastest growing fields. It shows how Firm j's competitive advantages in different technological fields are linearly related with the growth rate in these fields in the industry. If a firm focuses on patenting in the fastest growth fields, it has a higher position in the "leadership" of technological innovation in the industry.

$$RTA_{ij} = b_0 + b_j GrowthRate_i + u_i \,, \quad \text{for } \; i = 1, 2, \ldots, 25.$$

If b_j =1, it implies that Firm j innovates across fields in the same proportions as the industry does. If b_j >1, it implies that Firm j focuses more on the fastest growing fields than on average across firms in the industry. (They are innovating in the same direction as the industry.) If 0< b_j <1, the firm focuses more on the faster growing fields than the more slowly growing fields, but it is not as focused as are firms on average in the industry. If b_j <0, the firm specializes more in the slower growing fields. We define all the firms with b_j >1 as innovation leaders and the others as followers.

4.3 Independent variables: technological complementarity in the measurement of corporate technological coherence and absorptive capacity.

As suggested by Teece (1986), complementary assets are crucial in innovation. Followers with complementary assets can easily imitate or learn from leaders and accrue profits from innovation. Thus there is a need for the innovating firm to establish a prior position in these complementary assets. We study two types of complementarity here. One is the overall coherence of the firm's technological capabilities. It measures the firm's balance between exploration and exploitation in internal innovation. The other is the extent of specialization in those fields that are most related to the fastest growing fields, or the firm's absorptive capacity for the fastest growing fields. This index aims to measure the capacity for imitation or follow-on applications of developments that derive from the fastest growing fields.

To measure both overall coherence and absorptive capacity, we need first to identify the relatedness between any two technological fields in the biotechnology industry. We adopt the *ex post* measure of technological relatedness between fields proposed by Teece et al. (1994). The relatedness between any two technology fields i and k (R_{ik}) is:

$$R_{ik} = \frac{n_{ik} - m_{ik}}{s_{ik}}$$

Where: n_{ik} = actual number of linkages across firms between technologies i and k;

m_{ik} = the expected number of linkages between technologies i and k under the hypergeometric distribution; and

s_{ik} = standard deviation of the number of linkages under the hypergeometric distribution.

To calculate relatedness between each pair of technology fields, we include all biotechnology and pharmaceutical firms listed in either *NYSE* or included in *NASDAQ* 100 biotech-index during 2000-2004. After deleting 28 firms without a single patent and 16 firms that were not technologically diversified, 186 firms remained in the sample. These firms are active in 56 technological fields, with a total of 72,906 patents.

Of the 3,136 possible linkages between pairs of technology fields, 2,740 were actually observed in practice. A measure of relatedness (R_{ik}) was calculated for each such pair. R_{ik} ranged from 13.6015 to -1.6212. The average relatedness was 3.64 and the standard deviation was 2.62. Thus, the assumption of randomness can be rejected, in line with what has already been found by Teece et al. (1994) and Breschi et al. (2004).

Teece et al. (1994) suggested two measures for corporate coherence, the average of the weighted-average relatedness (WAR) and the average of the weighted average relatedness of neighbors ($WARN$). We use the WAR in calculating corporate technological coherence.[4] For a firm with m technologies, in technology i it has p_i patents, which field has an industry-wide relatedness R_{ik} with technology k. The weighted-average relatedness WAR_k of technology k to all other technologies within the firm is defined as follows:

$$WAR_k = \frac{\sum_{k \neq i} R_{ik} p_i}{\sum_{k \neq i} p_i}$$

Corporate technological coherence is then the firm's average *WAR* over the 25 active technical fields (*WARAVG*).

[4] As suggested by Breschi et al. (2004), in measuring global technological coherence, the WAR index is simple but its value depends on the number of technology fields in which the individual firm is active. The more technological fields the firm adds to its portfolio, the more "weak links" between those fields will be added to the index, thus lowering its value. $WARN$ avoids this issue by considering only those links that belong to the closest neighbors. We argue, however, that excluding "weak links" is a somewhat arbitrary loss of information. Moreover, if a "weak link" is weak because a new small field has been added then the weight assigned to combinations involving that field will be low. But for the fields with large numbers of patents then surely we should be interested in a wider measure of their relatedness with the full spectrum of other activities of the firm, rather than an overly narrow measure.

The most prominent opportunities for innovation exist in the fastest growing fields. The benefits that followers can obtain largely depend upon their absorptive capacity for these fastest growing fields. To identify the fastest growing fields, we select the top 9 fields (out of 25) according to their patent growth rates shown in Table 1. The relatedness of each of the 25 fields to the 9 fastest growing fields was measured by the *WAR* of each of the 25 fields to the 9 fastest growing fields.[5] In order to give greater weight to the absorptive capacity in the fastest growing fields that are of greatest relevance to each individual firm, we use an individual firm's patents in each of 9 fastest growing fields as the weights in calculation of its *WAR*. Absorptive capacity for the fastest growing fields is measured by the correlation coefficient from the regression of the firm's *RTA* distribution across the 25 fields on its *WAR* between the 25 fields and the 9 fastest growing fields.

$$RTA_{ij} = g_0 + g_j WAR_{ij} + v_i, \quad \text{for } i = 1, 2, \ldots, 25.$$

The magnitude of g_j shows how strongly that firm j's technological specialization is related to the 9 fastest growing fields. A higher g_j indicates that the firm has a higher absorptive capacity (*ACWAR*) for the fastest growing fields.

4.4 Control variables: core field participation, firm size and year

Cantwell and Santangelo (2000) have contended that there may be some categories of fast growing technologies in which specialization can bring rewards in general integrative capacity, where these fast growing technologies are themselves core to the ability to fuse or combine previously separate branches of innovative development – which is the facility provided by information technology (IT) today, much in the way that

[5] If it is one of the 16 fields that are not among the fastest growing its *WAR* is the weighted average relatedness with all 9 of the fastest growing fields, while if it is one of the 9 then its *WAR* is weighted average relatedness with the other 8 (excluding itself).

machinery technology did for much of the nineteenth century (Rosenberg 1976). However, it has also been argued that being locked into formerly successful general purpose systems (or core fields which grew rapidly in the past) may be negatively related to performance once there is a substantial shift in the underlying technological paradigm (Rosenberg, 1976; Cantwell, 1991).

Hence, we need to consider how the firm's technological specialization is related with the fields that are most central to its industry. A firm may innovate in the most dominant fields in terms of their absolute level of technological activity in the industry, or it may innovate in a niche position in the industry. There is empirical evidence that either of these strategies may be feasible (Pavitt, 1992; Pavit and Patel, 1997). Thus, we need to control for the extent of the firm's specialization in fields that attract the largest absolute levels of technology activity. This is measured by regressing the firm's *RTA* in each of the 25 technological fields on the shares of the industry's total patenting in the corresponding fields.

$$RTA_{ij} = r_0 + r_j PS_i + w_i \, , \quad \text{for } \; i = 1, 2, \ldots, 25.$$

where $PS_i = \sum_j P_{ij} / \sum_i \sum_j P_{ij}$. If $r_j > 0$, it implies that Firm j is relatively more specialized in the core fields of the industry, thus we may call it a "core player;" if $r_j < 0$, it implies that Firm j innovates more in the niche fields of the industry, thus we might call it a "niche player". Thus, r_j denotes the extent of core field *PARTICIPATION*.

The absolute size of the firm may also have an impact on its economic performance. In this industry, larger firms tend to outperform smaller firms. Therefore, we included the logarithm of total revenues to control for the size (*SIZE*). Also, two dummies (*Year99* and

Year04) were included to control for fixed effects associated with the differences between specific periods.

5. Results

Table 2 and Table 3 show the descriptive statistics and the Pearson correlation matrix of independent and control variables.[6] The results of the econometric estimates of the models are set out in Table 4. Table 4 shows the estimates of the coefficients of the independent variables, their standard errors, and the individual and joint significant levels.

[Table 2 here]

[Table 3 here]

[Table 4 here]

The main objective of this study is to highlight the role played by corporate strategies for technological innovation leadership and complementary capabilities (coherence and absorptive capacity) in the economic performance of firms. We ran 8 different models with various combinations of variables as shown in Table 4 to test the effects of innovation leadership, corporate coherence and absorptive capacity.

[6] Observing that the Pearson correlation between Leadership and Participation is as high as 0.888551, we must allow that it may cause a problem of multicollineaity. The model diagnostic tests for multicollinearity, though, indicate that multicollinearity is not a concern for these two variables. For all the models including Participation and Leadership in Table 4, only Model 7 shows that variation inflation factors (*VIF*) for Leadership and Participation are greater than 10 and the conditional numbers are greater than 15, which implies that Model 7 may suffer from a multicollinearity problem (although it is may caused by including interaction terms between variables.) The regression results do not change significantly (as shown in Model 8) if we exclude Participation. In fact, multicollinearity tends to cause the t-statistic to be biased toward insignificance because of the larger standard deviation of the estimates. Thus, if the t-statistic of a variable is significant in a model with a multicollinearity problem, we can tell for sure that the independent variable has a significant effect. To further investigate this problem, we also ran all the other models without Participation. Two of the rudimentary models for Leadership showed that the previously significant effect of Leadership somehow disappeared, which should not be the consequence of multicollinearity since that should work the other way if there was a problem. It may suggest that in the pre-models without considering all the combinations of strategies, Participation works as a proxy variable. Since Leadership shows no effect if we exclude Participation but shows a significant effect with Participation, these two variables may be confounding each other (since their effects on performance run in exactly opposite directions), and so it is necessary for us to control for one in order to check the effect of the other.

Model 5, Model 7 and Model 8 in Table 4 show that leadership has a significant and U-shaped quadratic relationship with the annual growth rate of stock prices. The firms that specialize in the fastest growing technological fields in the industry experienced higher economic performance, while the firms that do not focus their resources on the fastest growing fields also received higher market evaluation of their economic performance. The firms with poorest economic performance were those stuck in the middle. As suggested by Lee and Harrison's (2002) simulation study, a bimodal distribution of performance is evident when ordering firms by their degree of innovative leadership, which is likely to lead over time to a bifurcation of strategic groups into leaders and followers, since these are the most economically successful strategies (Hypothesis 1). As a follower, the firm has lower uncertainty about its R&D activities and its profits are more secure. As a leader, the firm faces greater risk but higher profits when they are realized. In Model 2, in which we consider leadership as the only independent variable, leadership exhibits a negative and significant linear effect on the growth rate of stock prices. This is the consequence of failing to control for the roles of coherence and absorptive capacity, on which the success of followers depends.

Table 4 shows that corporate technological coherence also has a significant and quadratic effect on the economic performance, which suggests again a bifurcation structure in corporate innovation strategies, in this context involving the relative balance between exploitation and exploration in constructing new combinations (Hypothesis 2). To achieve superior economic performance, a firm may allocate its R&D investment mainly to deepen and exploit existing capabilities. There is much evidence in the literature of this innovative strategy (Pavitt et al., 1989; Granstrand and Sjölander, 1990; Grandstrand et al., 1997). The firm may also search for new fields to enlarge its technology scope by bringing in as yet relatively unexplored combinations. This is consistent with the findings of Bosch et al. (1999) and Gilsing and Nooteboom (2006) that for newly emergent technologies like those in the biotechnology industry the focus of a firm's knowledge absorption may shift more towards knowledge exploration rather than exploitation. With all the uncertainties and opportunities, a firm with a larger scope and greater flexibility in its technological profile is more likely to create new values.

The interaction between these two innovation strategies is significant and positive (Models 5, 7 and 8). That is, at the same level of leadership, coherent innovators are likely to outperform experimental innovators; given the level of corporate technological coherence, leaders tend to grab more profits than followers. So there does appear to be some premium associated with innovative leadership when it is combined with a strategy of technological coherence, or in other words for leaders that hold a coherent combination of related capabilities around the fastest growing fields in which their activities are focused.

In the context of the above two innovative strategic choices between leading or following and between being coherent or experimental, having absorptive capacity will always be important no matter which strategic direction the firm adopts. Firms with absorptive capacity related to the fastest growing technological fields show a superior performance in the growth of stock price. It is thus critical for firms to establish absorptive capacity no matter where they decide to position themselves strategically in the composition of innovative activities in the industry.

The control variable for the extent of core field participation has a positive and significant coefficient, implying that the firms that are core participators in the industry tend to exhibit a higher economic performance than niche participators in the industry. There may exist strong opportunities for horizontal technological combinations and diversification, as it has been argued were obtained in some science-based industries historically (Pavitt, 1992). However, core participation plays no significant role in the most comprehensive Model 7, which suggests that it may also be acting as a proxy for excluded effects in sparser model specifications. *SIZE* is positive and significant. Recall that *SIZE* is calculated as the logarithm of total revenues in the period of interest. Thus, the firms with higher total revenues receive higher economic evaluation in the stock market. The dummy for the Year 2004 is significant and negative, which may show the effect of administrative time lags between patent application and grant.

6. Discussion and conclusions

The question we have addressed in this study is how the firm's strategies with respect to leadership in innovation and coherence in technological capabilities are related to the likely progress in the market's evaluation of a firm's value.

Previous studies have suggested that either leaders or followers may profit from innovation so long as they possess the appropriate complementary capabilities (Teece, 1986). It has also been suggested that firms in most industries will converge towards some pattern of technological coherence that is representative of the characteristics of innovation in the relevant industry (Teece et al., 1994). Our findings suggest that at least in the biotechnology industry market performance and selection may lead to a bifurcation of firms into strategic groups not only with respect to innovative leadership, but also to corporate technological coherence. That is, owing to the performance benefits of both high or low leadership and high or low coherence, a selection mechanism may operate that would drive firms towards clusters in one of four viable strategic combinations, as illustrated in Figure 1. Firms that evolve towards being Established Leaders, Radical Innovators, Traditional Imitators or Boundary-Spanning Followers may all tend to survive and to perform well.

[Figure 1 here]

Although in a stable environment firms may generally tend to build upon coherent technological bases, in a faster growing industry like that of biotechnology, it is possible that firms select an alternative and a more experimental technology base, but can still perform well. Innovation involves bringing about effective new combinations. To create innovative profits by introducing new streams of value added – and hence to realize performance benefits – firms may diverge to some extent in some consistent but unforeseen way from the typical patterns inherited from the past.

Absorptive capacity related to the fastest growing fields turns out to be the one systematic influence upon the ability of firms to profit from innovation in the industry. No matter which strategic group the firm has evolved towards, a prior position in the requisite complementary technologies is always an important condition for firms to execute their respective strategies successfully.

Our results have further shown that although much of the literature has rightly paid attention to the specific issues raised by the importance of being specialized in technologies which are at the leading edge of development or at the technological frontier (i.e. a focus on technological leadership); or to the importance of accumulative learning, inherited routines and expertise (reflected in a firm's overall coherence and absorptive capacity); or focused on the issues of size or breadth in the range of technological specialization; that it may be misleading to separately focus on just one of these factors treated in isolation. To obtain innovative profits, a firm is likely to benefit by clearly establishing itself as either as a leader or as a follower, and by pursuing a path of technological search that is either coherent or experimental, while always relying upon absorptive capacity for knowledge spillovers from the fastest growing fields in its industry.

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Table 1

The growth rate of patents application in the 25 technological fields

	Technological fields	Patent Class No.	total	No. of Patents Applied 1985-1992 (P1)	No. of Patents Applied 1993-2000 (P2)	Growth Rate= $\frac{P_2 - P_1}{(P_1 + 1000)}$	Rank
1	Food and Tobacco Products	127, 131, 426	426	235	191	-0.03563	18
3	Inorganic Chemical	423	165	122	43	-0.07041	22
4	Agricultural Chemical	71, 504	1007	468	539	0.048365	15
5	Chemical Process	23, 51, 62, 95, 117, 134, 156, 204, 205, 210, 216, 427, 432, 518	902	412	490	0.055241	13
6	Photographic Chemistry	430	351	269	82	-0.14736	25
7	Cleaning Agents and Other Compositions	106, 252, 507, 508, 510, 516, 588	993	539	454	-0.05523	21
8	Disinfecting and Preserving	422	119	32	87	0.053295	14
9	Synthetic Resins and Fibres	520-528	2213	1236	977	-0.11583	24
10	Bleaching and Dyeing	8	526	340	186	-0.11493	23
11	Other Organic Compounds	260, 530, 534, 536, 540, 544, 546, 548, 549, 552, 556, 558, 560, 562, 564, 568, 570	15396	6127	9269	0.440859	5
12	Pharmaceutical and Biotechnology						
121	Drug, bio-affecting and body treating compositions	424, 514	29970	9986	19984	0.910067	2
122	Chemistry: Molecular biology and microbiology	435	12717	2550	10167	2.145634	1
123	Chemistry: Analytical and immunological testing	436	637	143	494	0.307087	6
124	Multicellular living organisms and unmodified parts thereof	800	1202	131	1071	0.831123	3
13	Metallurgical Processes	29, 75, 148, 164, 228, 419, 420, 483	203	97	106	0.008204	17
14	Miscellaneous metal products	4, 16, 24, 30, 49, 108, 132, 206, 211, 215, 220, 248, 267, 279, 285, 312, 383, 403, 623	1149	432	717	0.199022	7
16	Chemical and allied equipment	34, 55, 68, 96, 118, 134, 156, 159, 202, 209, 210, 261, 366, 422, 451, 494, 502, 503	935	374	561	0.136099	9
18	Paper making apparatus	53, 162, 229, 493	202	78	124	0.042672	16
28	Other Specialized machinery	15, 30, 116, 140, 141, 221, 222, 227, 277, 300, 401, 425, 454	565	202	363	0.133943	10
29	Other General Industrial Equipment	91, 92, 110, 122, 126, 137, 165, 184, 192, 239, 251, 303, 415, 416, 417, 418, 431, 432	180	113	67	-0.04133	20
39	Other General Electrical Equipment	62, 136, 204, 219, 310, 318, 373, 388, 392, 429, 438	347	123	224	0.089938	11
41	Office Equipment and Data Processing Systems	235, 360, 365, 369, 377, 700-715	277	43	234	0.183126	8
49	Rubber and Plastic Products	152, 264	400	165	235	0.060086	12
50	Non-metallic Mineral Products	52, 65, 215, 241, 428, 501	762	407	355	-0.03696	19
53	Other Instruments and Controls	33, 73, 74, 128, 177, 235, 250, 324, 346, 347, 349, 351, 356, 359, 368, 374, 378, 385, 433, 600-607	5209	1741	3468	0.630062	4

Table 2

Descriptive Statistics

Variable	N	Mean	Std Dev	Sum	Minimum	Maximum
GROWTH the annual growth rate in the stock price	155	-0.09818	0.28233	-15.21852	-0.74432	0.58321
WARAVG corporate technological coherence	155	2.41707	1.34809	374.6465	-0.60843	5.36876
LEADERSHIP technological innovation leadership	155	0.37527	1.9241	58.16641	-20.02561	2.80418
ACWAR absorptive capacity in the fastest growing fields	155	0.95934	7.95951	148.6972	-39.88941	54.8337
PARTICIPATION core field participation	155	0.00133	0.00635	0.20656	-0.06128	0.00494
Size log of total revenues	155	12.07859	1.92936	1872	7.90295	17.28356

Table 3
Pearson Correlation Matrix

(N=155, Prob > |r| under H0: Rho=0)

	GROWTH	WARAVG	LEADERSHIP	ACWAR	PARTICIPATION	Size
GROWTH	1					
the annual growth rate in the stock price						
WARAVG	-0.07276	1				
corporate technological coherence	(0.3683)					
LEADERSHIP	0.06864	-0.17978	1			
technological innovation leadership	(0.3961)	(0.0252)				
ACWAR	0.0886	0.29021	-0.37018	1		
absorptive capacity in the fastest growing fields	(0.273)	(0.0002)	(<.0001)			
PARTICIPATION	0.15144	-0.21932	0.88551	-0.40201	1	
core field participation	(0.06)	(0.0061)	(<.0001)	(<.0001)		
Size	0.06504	-0.06028	-0.01571	0.19049	-0.09753	1
log of total revenues	(0.4214)	(0.4562)	(0.8461)	(0.0176)	(0.2273)	

Table 4

Economic Performance and Technological Innovation Strategies: Estimation of the Model

Parameter	1	2	3	4	5	6	7	8
Intercept	-0.281** (0.131)	-0.284** (0.127)	-0.239* (0.124)	-0.313** (0.138)	-0.277** (0.125)	-0.231* (0.128)	0.026 (0.152)	0.039 (0.132)
WARAVG corporate technological coherence	-0.066* (0.034)			-0.059* (0.036)			-0.176*** (0.042)	-0.180*** (0.039)
WARAVG*WARAVG	0.015** (0.006)			0.0143** (0.006)			0.029*** (0.007)	0.030*** (0.007)
LEADERSHIP technological innovation leadership		-0.060** (0.024)			-0.194*** (0.056)		-0.217*** (0.066)	-0.219*** (0.065)
LEADERSHIP*LEADERSHIP		-0.001 (0.001)			0.005* (0.003)		0.007** (0.003)	0.007** (0.003)
ACWAR absorptive capacity in the fastest growing fields			0.006** (0.003)			0.007** (0.003)	0.011*** (0.003)	0.011*** (0.003)
WARAVG* LEADERSHIP				-0.002 (0.005)	0.045*** (0.017)		0.065*** (0.023)	0.067*** (0.021)
WARAVG * ACWAR				0.002 (0.002)		-0.002 (0.004)	-0.009 (0.007)	-0.010** (0.004)
LEADERSHIP * ACWAR					0.001 (0.001)	-0.001 (0.001)	0.0001 (0.002)	-0.0002 (0.0018)
PARTICIPATION core field participation	3.613 (2.947)	13.817** (6.456)	6.112* (3.112)	9.324 (7.688)	15.245** (6.370)	5.839 (4.994)	1.825 (10.337)	
Size log of total revenues	0.033*** (0.010)	0.031*** (0.010)	0.024** (0.010)	0.034*** (0.010)	0.032*** (0.010)	0.024** (0.010)	0.029*** (0.009)	0.029*** (0.009)
Year 99	0.020 (0.062)	0.010 (0.062)	0.022 (0.062)	0.019 (0.062)	0.001 (0.062)	0.020 (0.062)	-0.010 (0.058)	-0.010 (0.058)
Year 04	-0.347*** (0.061)	-0.335*** (0.061)	-0.327*** (0.060)	-0.347*** (0.062)	-0.346*** (0.060)	-0.327*** (0.060)	-0.383*** (0.058)	-0.384*** (0.057)
N	155	155	155	155	155	155	155	155
R^2	0.3988	0.3977	0.3997	0.4023	0.4258	0.4012	0.5005	0.5004
Adjusted R^2	0.3744	0.3733	0.3795	0.3696	0.3943	0.3727	0.4583	0.4620
F statistics	16.36***	16.29***	19.84***	12.29***	13.53***	14.07***	11.86***	13.02***

*** p-value < 0.01
** p-value < 0.05
* p-value < 0.1

Figure 1

The Four Types of Innovation Strategies

		Coherence	
		Coherent	Experimental
Leadership	Leaders	Established leader	Radical innovator
	Followers	Traditional imitator	Boundary-spanning Follower