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Corporate knowledge diversification in the face of technological complexity: The case of industrial biotech☆

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ABSTRACT

In the course of late twentieth century, successive waves of molecular biological revolutions (recombinant proteins, monoclonal antibodies, genomics, proteomics, stem cells, tissue engineering, gene therapy) have emerged. As a result, technological knowledge base has become more complex. However, innovation and management studies have been ambivalent about this process. Part of the literature suggested that technological activity is highly industry-specific and accumulative. On the other hand, literature at the firm level has recognized that there has been corporate diversification. Such ambivalence reflects the tension between both micro process of technological diversification and technology convergence. One of the main empirical results of this paper is that inter-industrial convergence is localized covering some subsets of "industrial biotechnology" products. Secondly, patent data enable to distinguish between different kinds of corporate technology coherence: whereas health industry adopt conglomerate biotechnological diversification, industrial biotechnology corporations adopt a more coherent technology diversification enabling innovation and (dynamic) efficient growth.

1. Introduction

Towards the end of the 20th century, there were a series of revolutions in molecular biology (recombinant proteins, monoclonal antibodies, genomics, proteomics, etc.) that forced the major pharmaceutical, chemical, and agrifood groups to diversify their knowledge bases beyond their core capacities (Chesnais, 1981; Nightingale and Martin, 2004; Chandler, 2005; Ninghtingale and Mahdi, 2006). The dynamics of these technological revolutions have brought about a tension at the heart of neo-Schumpeterian approaches between an understanding of technological activity that is highly specific to each industry and the literature that analyzes groups' diversification strategies (Patel and Pavitt, 1997: 141; Patel, 1999: 8; Von Tunzelmann, 2006: 6).

This leads to the problem of complexity in the context of the theory of the firm. That is, how firms respond to the increasing complexity of their knowledge bases that results from the coexistence of different technologies. In light of this, the literature maintains, on the one hand, that firms can be understood as "adaptive complex systems" that can break down and specialize, simplifying their innovative activity so as to be manageable (Anderson, 1999). Other authors argue that when facing complexity, firms

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can diversify their knowledge base in a non-random fashion towards complementary technologies, thus ensuring a certain degree of coherence within themselves (Teece et al., 1992: 2).

Based on this discussion, this article asks whether the result of this tension between technological convergence and divergence is a single biotech paradigm that is shared by various industries, or if, in contrast, different paradigms that are highly specific (and complementary) to the pre-existing trajectories of each industry co-exist[1]. As such, a second question that arises is how firms respond to the increasing complexity of their knowledge bases, given the coexistence of different technologies. In particular, if large corporations have managed to consolidate a coherent knowledge base or have limited themselves to a conglomerate expansion in which different technologies become another asset in their financial portfolio.

To explore these questions, this paper is based on a methodological approach that uses patent data for a set of leading biotech firms to measure technological diversification. Section 2 contains a conceptual discussion of how the tension between specialization and diversification processes within large firms can explain the emergence of new technological paradigms. After the empirical framework has been presented, Section 4 considers how far there is a tendency for knowledge to converge into a single knowledge base that is shared by different industries. Section 5 analyzes whether this process is manifested in diversification strategies that are coherent with the knowledge base, or whether conglomerate diversification predominates among the different fields of biotech. It also considers how these strategies affect the pace of firms' biotech innovation. Finally, Section 6 presents conclusions and directions for future research.

2. Conceptual framework

Our starting point is the evolutionary theory of the firm, within which firms are understood as repertories of routines that define their own technological capabilities and their competitive performance (Nelson and Winter, 1982: 97). Through practice, repetition, and more or less incremental improvements, certain firms acquire capabilities in specific technologies. This allows the limits of the firm to be described above and beyond transaction costs, internalizing activities in which the firm has "core capabilities" that is, those innovation-, production-, and marketing-related activities for a limited set of products that the firm "knows how to do well" (Teece et al., 1992).

Although this perspective fills a theoretical void in neoclassical theory by explaining how firms innovate in a context of uncertainty, in certain circumstances when there is a change in the technological paradigm, firms must explore outside their prior knowledge base with greater intensity, seeking opportunities and orchestrating complementarities so as to create "new combinations." As Dosi argues (Dosi, 1988: 1133), in these circumstances, there is "a continuous tension between efforts to improve the capabilities of doing existing things, monitor existing contracts, and allocate given resources, on the one hand, and the development of capabilities for doing new things or old things in new ways."

In seminal literature of path dependency one technology is selected among a greater number of technologies.

This tension is expressed on both the theoretical and practical levels. In theoretical terms, two analytical perspectives can be identified in neo-Schumpeterian literature (Fai and Von Tunzelmann, 2001):

(i) First, studies that stress innovations as a *highly accumulative and stable pattern of technologies and activities* that are *specific to each industry* and that is the result of experimentation, experience, and interactions within firms or between the suppliers and users of new products (Patel and Pavitt, 1997: 141). From this point of view, innovation processes are *highly path dependent*, in that firms seek to solve their techno-economic problems in a way that is conditioned by their prior technological problem-solving experiences, giving rise to sector-specific knowledge bases. As a consequence firms (and industries) would show persistent and stable activities and technologies' portfolios.
(ii) Second, there are a wide range of studies that point out that the diversification of the knowledge base is a key feature of large firms' strategies (Fai, 2001; Fai and Mendonca, 2010). When unexploited scientific and technological opportunities and/or problems that cannot be solved using existing technology arise, firms broaden their knowledge base beyond the technologies that are specific to their products, resulting in a technological diversification that is greater than their productive diversification (Patel, 1999: 8; Tunzelmann, 2006: 6).

Several authors recently have acknowledge that even if path dependency has a constraining effect on firm's strategies, there are space to creativity and certain big corporations are able to influence the course of events, can generate new paths through technological diversification (Fai and Von Tunzelmann, 2001; Araujo and Harrison, 2002; Antonelli, 2009; Garud et al., 2010). Consequently, it's possible to admit the coexistence of multiple paths that can eventually converge (or not). For example some multi-propose technologies, such as biotechnology, have the potential to affect the potential of several paths and literature on industry convergence seems to suggest that a creative synthesis of several technological paths can generate new paths, e.g.: the emergence of "functional foods" and

[1] Dosi (1982: 147) defines a technological paradigm (a term based on Kuhn's concept of a scientific paradigm) as a techno-economic problem-solving "pattern" based on highly selective natural science principles, together with specific rules that are oriented towards acquiring new knowledge and safeguarding it from competitors wherever possible Technological paradigms define a knowledge base that has resulted from different scientific opportunities for future innovations, on the one hand, and on the other, from a limited set of heuristics or search procedures regarding how to take advantage of these opportunities and ensure that they are appropriated.

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"nutraceutics" at the boundary between food and pharmaceuticals (Curran and Leker, 2011).

2.1. Firms' technological diversification and the emergence of technological paradigms

This tension between *path dependence* based on earlier technologies and firms' *technological diversification* can be analyzed empirically from the perspective of the technology diffusion cycle (Abernathy and Utterback, 1978: 40; Afuah and Utterback, 1997: 183). In the initial phase of a new technology, the focus of inter-firm competition is product innovation, relying on the technology used in existing processes. In the particular case of biotech diffusion in chemical-based industries like the ones analyzed in this article, product innovations necessarily require radical complementary process innovations (Chesnais, 1981; Chandler, 2005: 260). In this case, firms diversify their knowledge bases right from the initial stages in order to find solutions to new problems. As they move through the cycle of paradigm development, the technology stabilizes and innovation becomes incremental through learning based on existing knowledge. Up scaling, Practical production-based learning and knowledge related to regulatory issues become more important than formal R&D-based knowledge. Cost advantages come to dominate the competition. During these stages, innovation becomes strongly path dependent and "dynamic" absolute costs advantages barriers to entry are raised.

It thus can be argued that during the emergence of a new technological paradigm until the point at which it has been fully established, firms transition from high path dependence regarding existing knowledge bases to greater technological diversification. This process of technological diversification within a given sector may or may not be accompanied by the convergence of existing sectoral knowledge bases into a set of heuristics that is shared by all the industries. Once the technological paradigm has been established and begins to be consolidated, this diversification starts to decrease and innovation becomes incremental in solving process bottlenecks, thus reinforcing path dependence again. In line with this line of analysis, some authors recently argued than this dynamics explains a transitory growth of "non related diversification" of corporate's knowledge base then gradually compensated by a "related diversification" process (Krafft et al., 2011).

As a consequence of technological diversification, the technological paradigm is not necessarily limited to a single sector. Instead, depending on how the paradigm develops, opportunities may arise for the diffusion of the paradigm to other sectors, leading to the emergence of new industries and the adoption of the paradigm by other pre-existing industries (Freeman and Perez, 1988: 38). Therefore, for a set of sectoral technological paradigms to converge into a technological system, the combination of the different technologies must allow a common knowledge base to emerge, together with a set of R&D heuristics that are shared by several industries, thus enabling the advent of new productive processes and key inputs that allow for significant reductions in costs.

2.2. Coherent diversification versus conglomerate diversification: Corporate technological strategies in the face of new technological paradigms

Up to now, this paper has stressed the technological diversification of large firms, leaving aside the greater complexity of technologies and markets that results from successive waves of new technologies. In order not to be overtaken by rivals, firms can undertake different sorts of strategies to tackle increased technological complexity.

Other authors argue that technological diversification may be an appropriate response in a highly competitive context provided that the knowledge base is coherent (Teece et al., 1992). The concept of coherence allows us to reconcile the localized nature of learning with new waves of technological opportunities that oblige firms to generate new technological capabilities. As with the perspective described above, firms focus on a certain set of technological knowledge that is defined by their core competences. However, they incorporate a set of secondary technological capabilities that complement these core competences. Under certain circumstances in technological paradigm changes, secondary capabilities in new technologies can become core competences, serving as "pivots" for changes in firms' technology portfolios. From this point of view, firms gradually diversify their technological capabilities and modify their knowledge base according to the complementarities between core and secondary technologies, while maintaining a certain level of coherence to their knowledge base beyond a portfolio of random technologies.

Technological coherence is not a feature that is shared by all large firms, and depends on the competitive context in which they operate. The last few years have witnessed a strong process of acquisition and merger of biotech firms by or with leading groups from the chemical, pharmaceutical, or grain trade. These processes lead to strategies of conglomerate diversification that can only be viable in the context of low levels of selectivity among competitors that is associated with the presence of industrial and regulatory barriers to entry.

A conglomerate diversification strategy would only be viable in those competitive contexts in which large groups manage to maintain high regulatory barriers or control complementary assets, as is the case for certain pharmaceutical groups. In a context of low barriers to entry, the strength of the competition will force large groups to adjust their technology portfolio or lose part of their market share.

This article asks whether, as a result of the tension between convergence and divergence in the knowledge base, we are now facing a single biotech paradigm that is shared by various industries, or if, in contrast, different sectoral paradigms co-exist and are highly specific (and complementary) to the preexisting trajectories of each industry. The second question arises in the context of the uncertainty associated with the coexistence of difference knowledge bases; namely, whether the leading firms in the biotech diffusion sectors have managed to consolidate a coherent knowledge base that will allow them to transform technological opportunities into new products and processes, or whether they have limited themselves to a

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conglomerate expansion in which different technologies have been assimilated as mere assets within a financial portfolio.

3. Methodology and database

In order to analyze the degree of convergence between different industries' biotech knowledge bases and firms' microeconomic responses, the chosen methodological approach uses patent data as a "proxy" indicator. According to Fai (2003), patents are a good measure of cumulative (persistent) technological development because they provide data over long periods and they require comparatively low degree of novelty and, therefore, are able to reflect incremental change processes. Patents have also been used in previous technology and innovation studies as an indicator of the composition and evolution of knowledge bases (Graff, 2002; Saviotti, 2002).

Other studies have performed extensive reviews of the advantages and disadvantages of patents as an indicator of knowledge bases. The only additional observation to be made in this regard is that the most relevant of the usual criticisms is the fact that the propensity to innovate varies from one sector to another and is not necessary a good indicator of knowledge novelty. Patents are used as strategic entry deterrent by incumbents as well as financial market "signaling" by small firms wishing to open their capital. In other words, the propensity to file for patent is not the same in the chemical/pharmaceutical industry as in metal mechanics, nor is that of a large firm from a developed country the same as that of an independent firm from a developing country. The bias of this study has been reduced by limiting the analysis to firms from developed countries operating in sectors with a high propensity to file for patents.

In order to define the biotech knowledge base, the OECD definition of biotech was used, based on the international patent classification (IPC). IPC codes are assigned to patents by evaluators at patent offices. Although perceptions vary from one evaluator to another, they generally agree on classification criteria. This allowed IPC codes to be taken as units of analysis and to be grouped into different biotech areas according to the classification outlined in Annex 1.

In line with Graff (2002) and Fai and Von Tunzelmann (2001) we adopt the number of firm's IPC biotechnology class codes as a proxy of industry's "biotechnology capabilities" in each area. We assume that capability accumulation is one of the main sources of knowledge base and the persistence of technology pattern can represent path dependence phenomena (Fai, 2003). This methodological choice is complementary with social networks analysis which assumes that knowledge creation is more a knowledge recombination activity than a technology accumulation phenomenon (Saviotti, 2004; Saviotti, 2007)[2].

The sample is made up of a selection of 43 firms that operate in different areas of industrial biotech application and represent more than 50% of biotech sales in each industry: the pharmaceutical industry, the food industry, the manufacture of enzymes, and biomass applications in biopolymers and other substitutes for chemical-based inputs[3]. The information source used was the list of approved patents by the U.S. Patent and Trademark Office (USPTO) and systematized by the Delphion database. The choice of the U.S. patent office is justified by the fact that the U.S. economy is an area into which any firm wishing to grow and compete at the global level will want to expand. The decision to use approved patents rather than patent applications is justified by the fact that while the applicant firm assigns the application to a technological field according to more or less subjective (or intentional) criteria, in the case of approved patents, the evaluators from the patent office are who decide on this field. We are sure this methodological choice does not arrive to totally solve the "strategic bias" of patents but it could reduce it in some extent. As such, for the set of preselected firms, this study first identified patents issued between 1980 and June 2009 corresponding to the OECD definition of biotech (see Annex 1).

4. The evolution of technology at the sectoral and microeconomic level: Some results in the light of patent indicators

When analyzing the different stages of a technological paradigm, the technological opportunities generated are seen to be characterized by a period of rapid growth followed by another of more moderate growth, forming a sort of S-shaped curve that is followed, in turn, by a decline (Andersen, 2000: 30). Patent stock is an approximate indicator of the opportunities that are opened up by technology, which should not be confused with the curve for the diffusion of products on the market (Graph 1)[4].

The scale and pace at which biotech opportunities appear varies according to their areas of application. The scale of opportunities is significantly greater in the case of pharmabiotech than for other applications. In turn, biotech opportunities do not evolve over time in the same way in each of the three sectors. The time pattern for technological opportunities for food ingredients and enzymes shows an initial phase of expansion towards the end of the 1990s, following which growth rates slowed down, before stagnating

[2] This approach sustains that the knowledge base structure can be described by a number of nodes and their relationships. As several authors argue recombination is one side of the coin as soon as knowledge change is necessarily the result of both internal (learning and R+D activity) and external knowledge socialization and recombination (Cohen and Levinthal, 1989; Antonelli, 2001; Antonelli, 2002). As a consequence biotechnology capabilities accumulation in each technology class can be also a proxy measure of knowledge base structure.

[3] The focus of the selection are diversified multinationals or specialized biotech firms, based on a case study carried out as part of the PICT project "The potential of biotech for industrial development in Argentina".

[4] This curve should not be confused with that of diffusion. While the diffusion curve shows the actual creation of new products on the market, the opportunity curve only reflects potential developments, as indicated by patent stocks. In line with Graaf's study (Graff, 2002: 10), it has been established ad hoc that once 13 years have passed since a patent was issued, the opportunities it represents no longer generate specific advantages for the firm in question but instead tend to form part of the knowledge that is freely available to all.

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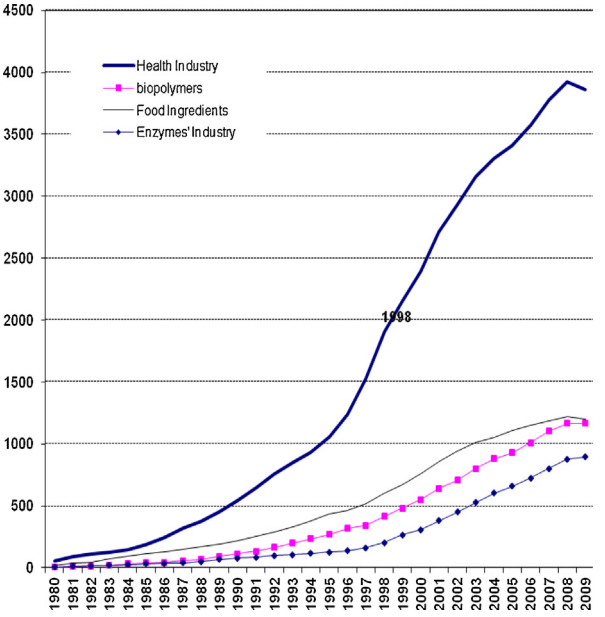

Graph 1. *Industrial Biotechnology:* stock of patents granted by the USPTO. *Source:* Based on patents granted by the USPTO and the DELPHION database.

by 2008. In the case of biopolymers, the patent stock has shown a steadier (i.e. less cyclical) rate of growth than in the other sectors. The situation is notably different for the pharmaceutical industry, which shows successive waves of opportunities that never reach maturity.

It is to be expected that these evolutions in the scale of biotech opportunities be accompanied by changes in the structure of the knowledge base, depending on the field in question, and that some areas of knowledge are more important than others.

4.1. Accumulativeness and convergence between different applications of industrial biotech

This section tackles the question set out in Section 2, namely how far the structures of knowledge bases show convergence processes between different industries, giving rise to the emergence of a shared biotech paradigm, or whether, instead, differentiated sectoral technological trajectories persist.

4.1.1. The evolution of the structure of the knowledge base

Before sector-specific processes are analyzed, it is of interest to show how the composition of the joint knowledge base has changed over each of the three decades of biotech diffusion (the first three columns of Table 1). The chart shows how the relative importance of the different biotechnologies has changed during the period. Changes in the structure and hierarchy of the different technologies were more notable between the 1980s and 1990s than between the 1990s and the first decade of the 2000s. This would appear to indicate that after an initial phase in which firms incorporated new knowledge, from the 1990s onwards they stabilized into a more or less

Table 1
Biotechnology knowledge base composition (ranking in order of patent classifications).

Technology	Industry																	
	Total			Enzymes			Health			Bioplymers			Food ingredients		
	1980–1989	1990–1999	2000–2009	1980–1989	1990–1999	2000–2009	1980–1989	1990–1999	2000–2009	1980–1989	1990–1999	2000–2009	1980–1989	1990–1999	2000–2009
Micro-organisms	2	1	1	2	1	1	4	4	4	2	1	1	2	1	1
Peptides (MAB)	4	2	2	5	5	5	2	1	1	3	4	5	6	6	6
General genetic engineering	7	5	3	9	4	3	6	5	5	7	2	2	5	4	4
Bioprocessing	1	3	6	1	2	4	5	7	6	5	6	4	1	2	2
Enzymes	3	6	4	3	3	2	7	6	7	8	5	3	4	3	3
Biological Measuring or testing	5	4	7	6	8	7	1	2	3	1	3	10	7	8	7
Medicinal Preparations	6	7	5	4	6	10	3	3	2	4	7	12	3	7	8
Cell lines and Tissues	8	8	8	10	9	8	8	8	8	9	10	8	11	9	9
Encoding enzymes or proenzymes	10	9	9	11	7	6	11	9	10	12	11	9	8	5	5
Genes encoding plant proteins	12	10	10	12	11	9	10	11	11	13	9	6	12	11	10
Processes modif	9	11	12	13	13	12	13	13	14	11	8	7	13	14	12
Microbiology instruments	13	12	11	8	10	11	9	10	9	6	12	13	9	10	11
Tissue culture	14	13	13	14	14	14	14	14	13	14	14	11	14	12	14
Biorremediation	11	14	14	7	12	13	12	12	12	10	13	14	10	13	13

organized pattern or heuristics from which innovations can be developed.

A detailed analysis of the composition of the knowledge base reveals a set of third-generation biotechnologies that were not particularly significant in the 1980s, the importance of which increased significantly until reaching their present position among those that are attracting the most interest in the industry. Noteworthy cases within this group include recombinant DNA techniques and genetic engineering, which moved up from seventh to third place in the ranking. Peptide development has also become more important, though to a lesser degree, largely due to the development of monoclonal and polyclonal antibodies. Finally, certain biotech techniques that were highly significant at the start of the study period have become less so, such as biological tests or measurement devices, which ranked first during the 1980s but moved to sixth place in the 2000s.

It must be stressed that there is also a great degree of continuity in the composition of the knowledge base. Certain first- and second-generation biotechnologies (microorganisms, enzymes, bioprocessing) have occupied an important position in the structure of the knowledge base throughout the period. The identification and use of different microorganisms continues to be crucial, even after the diffusion of genetic engineering[5]. In turn, enzyme technologies with applications in different industrial uses and bioprocessing technologies have also remained relevant within the structure of the knowledge base. This demonstrates that independently of the emergence of third-generation biotechnologies like genetic engineering and then genomics, there are a set of complementary first- and second-generation technologies in which firms had accumulated capabilities, and it is precisely the ability to take advantage of these complementarities that enables groups to gradually diversify their knowledge base and guarantee coherence.

4.1.2. Accumulativeness and path dependence in biotech applications

It can be inferred from the above analysis that the tension between the path dependent nature of the knowledge base and prior technology and the appearance of new technologies like recombinant DNA has been present to varying degrees throughout the period of study.

To illustrate this tension more synthetically, the statistical correlation ρ between the composition of the industry knowledge base was estimated for the 1980s, the 1990s, and between the 2000s and the 1990s. This indicator was used as a proxy index of path dependence of knowledge base[6]. Should the correlation be close to one and statistically significant, the industry knowledge base has a high degree of path dependence. That is, new developments and/or technologies would be dependent on the prior knowledge base. This aspect reveals, on the one hand, that technological opportunities are explored in each industry in a context of prior learning and, on the other, that innovative activities show increasing dynamic returns, and that the greater the accumulation of knowledge in a certain combination of disciplines, the greater the probability of reaching innovations.

Table 2
Biotech industries: the persistence of the industry knowledge base.

Correlation of industries knowledge base (value of ρ)		
Industry	KB 1990s on KB 1980s	KB 2000s on KB 1990s
Enzyme's industry	0.80**	0.91**
Health biotech	0.76	0.98**
Bioplymers industry	0.47*	0.89**
Food ingredients	0.79**	0.91**

* Correlations are significant at 10% level.
** Correlations are significant at the 5% level.

The emergence of biotechnology in the industries analyzed, particularly in health applications, began between the second half of the 1970s and the first half of the 1980s, a period for which no information is available. It is possible to use existing data to analyze how, after a period of strong path dependence, coefficient ρ must decrease as firms expand their knowledge base, identifying new problems and finding new solutions to pre-existing techno-economic problems (Table 2).

As can be seen, the composition of the human health knowledge base during the 1990s does not appear to be correlated with that of the 1980s. This indicates a restructuring of the knowledge base during that period and weak path dependence in comparison with prior heuristics. Path dependence is relatively greater in the enzyme and food ingredients industries, in which the cumulative and localized nature of the process of seeking solutions seems to prevail. In contrast, between the 1990s and the first decade of the 2000s, there was a notable increase in path dependence, which is reflected for all industries in autocorrelation indexes that are close to one and significant at 1%. This shows that although firms continue to explore new biotech fields, the effects of accumulativeness dominate in all sectors, with the potential for increasing returns in all the applications analyzed[7]. As will be discussed in Section 5, this potential will only be effective in terms of the degree of coherence of the knowledge bases of the groups involved in each industry.

[5] Microorganisms (such as yeasts or bacteria) serve as systems of expression for genetic engineering in that they continue to be used for the multiplication of new molecules.

[6] There are other computational methods used to identify trends and path dependence using a computational network based approach. For example Krafft et al. (2008) suggest network based indicators based on a combinatory view of knowledge base. In the same way, the work of proposes a very insightful method to detect emerging technology domains. These kinds of measures are based on publication co-citations time patterns. Though this method probably could be extended to the case of patents, the extension is not automatic because co-patent citations could represent a common technology domain but also property rights differentiation firms strategies. Patents seek usually to show that the new patent claim is different from the cited patent.

[7] These results are consistent with Krafft et al. (2011) findings of a "non related" knowledge base diversification between 1980 and 1985 that then converge with the degree of "related diversification".

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Table 3
Biotech industries: inter-industry correlation coefficient matrices and technological convergence between industries.

Industry	Average 1980s		
	Enzyme's (%)	Biopolymers (%)	Food Ingredients (%)
Health biotech	31	**93.3****	35
Enziyme's		28	**87.8****
Biopolymers			32
	Average 1990s		
	Enzyme's (%)	Biopolymers (%)	Food ingredients (%)
Health biotech	**62.3***	**75.5****	42
Enziyme's		**79.8****	**95.4****
Biopolymers			**73.1****
	Average 2000s		
	Enzyme's (%)	Biopolymers (%)	Food Ingredients (%)
Health biotech	42	37	40
Enziyme's		**90.1****	**97.2****
Biopolymers			**86.9****

* Correlations are significant at 10% level.
** Correlations are significant at the 5% level.

4.1.3. *Convergence of the knowledge base for industrial biotech applications*

It is to be expected that in those periods in which each industry showed a high degree of path dependence, the possibility of the different knowledge bases converging is limited. In contrast, if the diversification of groups leads to the modification of the knowledge base by adopting new technologies, there is a possibility of convergence and the emergence of a new technological paradigm. One way of measuring the degree of convergence between the knowledge bases for the different applications is by estimating the statistical correlation between the structures of the knowledge bases for the different industrial applications for each period.

This estimation was carried out for all three decades, and two different situations were identified. On the one hand, applications of industrial biotech in the production of enzymes, biopolymers, and food products show growing convergence between 1980 and 1990, which is consolidated during the 1990s and into the 2000s. On the other, the biopharmaceutical industry experienced a temporary convergence: its starting point was a knowledge base that was different to that of most other industries during the 1980s, from which it moved towards convergence during the 1990s, only to diverge again in the 2000s (Table 3).

During the 1990s, technological convergence grew while the accumulativeness of R&D decreased in all industries between then and the 1980s. Up until the 1980s, industrial biotech firms manufactured biopolymers and biocatalyzers – enzymes – by identifying existing microorganisms using extractive methods. The irruption of molecular biology and modern genetic engineering towards the end of the 1970s in the area of human health led firms in these industries to diversify their S&T knowledge base to include these new technologies, which had previously been outside their domain. For example, during the 1990s, this allowed enzyme production from genetically modified microorganisms to substitute extractive methods. As a corollary, the diversification of the knowledge base for applications of biopolymers and enzymes led to a convergence of their technological competences with those of the health industry.

During the 2000s, while industrial biotech applications merged into a common technological paradigm, the convergence in human health applications was reversed. The pharmaceutical industry increased R&D in biotech areas that are secondary in other industries, such as the development of monoclonal antibodies and the medicinal applications of these. The health industries diverge from the knowledge base of other applications, thus limiting the emergence of a shared biotech paradigm that could give rise to a set of shared common search heuristics. As such, it can be argued that an "industrial biotech paradigm" has emerged which is limited to applications in biopolymers, enzymes, and food ingredients[8].

5. The technological strategies of the main industrial biotech firms

Firms respond in a variety of ways to this partial convergence between different industrial biotechnologies, conditioned by their prior microeconomic trajectory. In a context in which the fields of knowledge needed to develop new products are multiplying, firms can respond in a number of ways to this growing technological complexity. As was discussed in Section 2, firms undertake technological diversification strategies that may be coherent or conglomerate depending on their ability to take advantage of the complementarities between different technologies. The indicators for diversification and technological coherence are defined in Box 1.

[8] This convergence and limited divergence behavior matches with Krafft et al. (2011) results in which the relative similarity index has increased and the cognitive distance has decreased up to 1990.

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Box 1: Regression variables

LogPat00 = Logarithm of the patent flow between 2000 and 2009 (number of patents issued). This is the dependent variable for the estimations and reflects the creation of new knowledge.

Stock90 = Logarithm of the patent stock accumulated between 1980 and 1999 (number of patents issued). This is used as a control variable of firms size and reflects the size of the knowledge base that each firm has accumulated in the past and on the basis of which is more likely to innovate and increase the knowledge in the present.

Diversification = This is an indicator of the diversification of the knowledge base, which is calculated by subtracting the Hirschman Herfindalh index from one (1-HHerf). The greater the HHerf indicator, the greater the more specialized the knowledge base is, the 1-HHerf indicator shows diversification.

Coherence = Indicator of the coherence of the firm's knowledge base. This measures the degree of complementarities between the different forms of knowledge that the firm has accumulated throughout the period of study, based on the coherence indicator for the technological knowledge base defined by Saviotti (2002). If two types of biotech are used together, they are assumed to be complementary and thus coherent. Therefore, if the two technologies i and j are complementary, it is assumed to be more probable that they will occur together than if they are not related. Given the probability that the two technologies are used together with an expected value of μ_{ij} and typical variation σ_{ij}, the coherence between technologies i and j is given by COH_{ij}:

$$COH_{ij} = \frac{C_{ij} - \mu_{ij}}{\sigma_{ij}}$$

In which C_{ij} represents the frequency of with which technologies $_i$ and j co-occur. The firm's level of coherence is the average coherence between all COHPP technologies in which P_j is the importance of technology within the knowledge base.

Pathdep = path dependence coefficient, measuring the correlation between the structure of the biotech knowledge for patents issued to the firm between 1990 and 1999 and the structure of patents issued 2000 and 2009.

Alianza = percentage of patents that the firm shares ownership of. This variable measures the degree of horizontal collaboration with other firms or research institutions (i.e. those with similar levels of economic power) in order to achieve the developments in question throughout the entire period under analysis.

Farma = qualitative variable that reflects whether the firm belongs to the biopharmaceutical sector.

Bioind = qualitative variable that reflects whether the firm belongs to biopolymer and/or enzyme sectors.

Although there is considerable heterogeneity in the productive strategies of the different industries that use biotech applications, there is a propensity among the leading firms in each industry to develop a diversified, coherent knowledge base. In the cases of large diversified groups in the pharmaceutical and food industries and/or large diversified grain or biopolymer traders, there is a dynamic that is more associated with conglomerate expansion, in which technological diversification does not seem to be accompanied by the development of complementarities between the different biotechnologies, resulting in low levels of coherence. In sum, firms' technological strategies can be classified according to their degree of diversification and coherence, as shown in Fig. 1.

In order to evaluate how far innovation is determined by technological diversification or by the coherence of the knowledge base, a cross section was estimated for the determinants of biotech innovation for the 43 firms from the different industries included in the sample. The model combines information on the innovative performance of these firms, the structure of their knowledge bases, and the strategies the effects of which on innovation this paper seeks to unravel, but always restricting variables to those in the firms' own knowledge bases.

$$\begin{aligned} \text{LogPat00}i = {} & \beta 0 + \underset{(+)}{\beta 1\,\text{LogStock99}\,i} + \underset{(?)}{\beta 2\,\text{Logpathdep}} \\ & + \underset{(?)}{\beta 3\,\text{Logdiversif}\,i} + \underset{(+)}{\beta 4\,\text{Logcoherenc}\,i} \\ & + \underset{(+)}{\beta 5\,\text{alianza}\,i} + \text{u}i \end{aligned}$$

The variables to be used are presented in Box 1. The dependent variable is the patent logarithm between 2000 and 2009, which is considered a proxy variable for firms' competitive performances. In order to control the size of the knowledge base firm we introduce the firms patent stock up to 1990.

The diversification of the knowledge base (diversif) and coherence (coherenc) are included as strategic variables. Following on from the discussion in Section 2, technological coherence is expected to have a positive effect on the propensity to innovate. In turn, technological diversification is expected to have an ambiguous effect on the rhythm of innovation, given that, on the one hand, when the knowledge base expands, the probability of innovating increases due to the incorporation of new technological tools, but on the other, this increased diversification generates a negative effect on innovative performance by reducing the coherence of the knowledge base. This is due to the difficulty in taking advantage of complementarities between different areas of biotech when the complexity of the knowledge base increases, making the innovative process less efficient. Bearing this possibility in mind, a multiplicative variable has been introduced as an independent variable between coherence and diversification in order to capture the marginal effect of diversification on the effect of coherence.

The results of the estimation are presented in ordinary least squares in Table 4. As was to be expected, the size of the knowledge base has a positive effect on innovation in all four regressions. Path dependence does not have a significant positive effect. As such, the prior trajectory does not seem to affect the probability of innovating, which may be captured by the variable dummy for industry. The alliances with other firms that are captured by co-owned patents are also not determinants of the propensity to innovate, which is not to say that other sorts of cooperation

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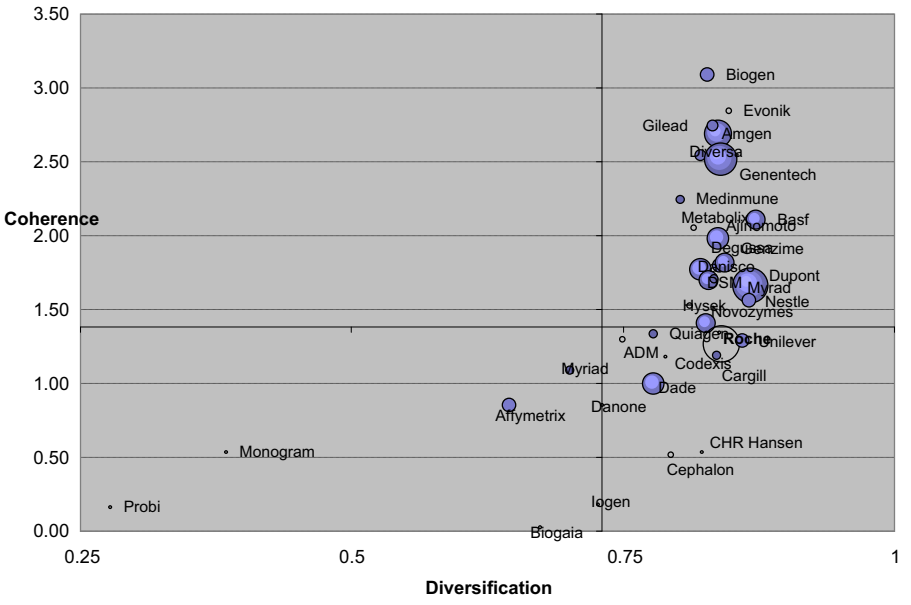

Fig. 1. *Industrial biotech:* firms' strategies according to their diversification and coherence. *Source:* Based on patents granted by the USPTO and the DELPHION database.

Table 4
Industrial biotech: OLS estimation.

Dependent variable: log (pat00)				
	(1)		(2)	
Variable	Coefficient	*t*-Stadistic	Coefficient	*t*-Stadistic
C	4.832389	1.873044*	7.122567	2.625049**
LOG(STOCK90S)	0.644047	7.746552***	0.708353	8.286152***
LOG(PATHDEP)	−0.440552	−0.862176	−0.768887	−1.497593
LOG(COHER)	0.665532	4.245230***	1.504784	3.336886**
LOG(DIVERSIF)	−0.728439	−1.500361	−1.269988	−2.364954**
LOG(DIVERSIF) × *LOG(COHER)*	–	–	−0.570572	−1.971806*
ALLIANCE	−0.000945	−0.573110	−0.000391	−0.245754
BIOPHAMA	0.259960	1.075828	0.583196	0.481010
BIOIND	0.588584	2.294407**	0.115925	2.391754**
n	43		*n*	43
R^2	0.897173		R^2	0.910549
Ajusted R^2	0.870514		Ajusted R^2	0.883026

* Statistical significance at 10%.
** At 5%.
*** At 1%.

agreements in which ownership is not shared – such as in smaller laboratories and SMEs – might not generate a positive effect.

As was expected, technological coherence had a significant positive effect on innovation. With regard to the effect of technological diversification strategies, the results show that this has a significant negative effect on propensity to innovate. In addition, in the second case, the multiplicative variable between coherence and diversification is significant and negative, which could be interpreted as an indirect negative effect of reducing the effect of coherence on the knowledge base. This result validates the hypotheses that had been deduced from the review of the literature in Section 2, namely that conglomerate technological strategies or portfolios of non-complementary projects are not sustainable in a relatively demanding selection context (Table 4).

Finally, the sectoral control variables verify that while industrial biotech applications have a significant positive effect on innovation vis à vis food applications, pharmaceutical applications have a non-significant negative effect. This result is in keeping with the conclusions of Section 3 regarding the consolidation of the biotechnology paradigm in industrial applications, as is manifested by these industries' greater propensity to innovate.

6. Conclusions

This study has allowed us to produce a set of results that are relevant to illustrate the degree to which the

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biotech paradigm has been consolidated and the possibilities for the expansion of biotech in developing countries. Some 30 years on from the emergence and inter-sectoral diffusion of these technologies, there is no single technological paradigm, but rather multiple sectoral innovation trajectories. This study has confirmed that the diffusion of biotechnologies is not homogenous over given periods nor according to the sectors where these technologies are applied. As such, it provides some preliminary diagnostic components for technological policies in developing countries.

From the sectoral point of view, there is a tendency towards convergence among the technological paradigms of the enzyme, biopolymer, and food industries, which reveals the consolidation, in these industries, of exploitation strategies for economies of scope, based on problem-solving heuristics for technical problems containing shared biological areas. In turn, biotech applications in the health sector reflect a different dynamic. Although their knowledge base converges with those of the other industries in the 1980s and 1990s, a differentiation process began to emerge again from 2000 onwards. Biotechnological opportunities in the health sector show the greatest growth, which despite also being highly path dependent from 2000 onwards with regard to the knowledge base of the 1990s show important changes in the knowledge base towards areas that are not of interest (for now) to industrial biotech activities. Entry as product imitators (by low cost process innovation) is one of the main alternatives to developing countries firms but it's not the only opportunity opened. Alternative technological paths in health biotechnology have been developed in the past two decades including both new process and product niche innovations.

Furthermore, this study has confirmed the theses of the evolutionary literature that claimed that there was no one-to-one relationship between productive diversification and technological diversification. In this sense, diversified firms with conglomerate strategies coexist with others with coherent strategies. When the effect of strategy type on the pace of innovation is estimated, it is reveal that coherence is what most explains leading biotech firms' propensity to innovate. This shows that low levels of exploitation of the complementarities between different technologies within large groups with conglomerate strategies limits the rate at which new technological knowledge is created.

Relevant topics for future research include exploring how far coherent groups' greater propensity to innovate translates into noteworthy increases in productivity and cost reductions, thus generating effective conditions for replacing the techno-economic paradigm based on cheap oil and chemical synthesis.

From this set of conclusions, it can be inferred that when there is a biotech paradigm that has been consolidated for certain industrial applications, the possibilities of entering those sectors are limited. Dominant groups have already established a set of routines, procedures, and heuristics which translate into a greater propensity to innovate. Pharmaceutical industry, which has not consolidated a shared knowledge base with other industries and includes large groups with conglomerate strategies that survive in the context of high regulatory and intellectual property barriers, independent firms (including those from developing countries) still enjoy a certain degree of temporary freedom to enter international markets as new regulations are established, using strategies that manage to combine a coherent knowledge base and learning related to production and to the regulatory context. As such, future analyses would need to undertake firm-level developing countries' case studies to identify the potential and limits of this type of strategy.

Appendix A. Annex 1: Groups of biotech IPCs.

The OECD definition includes a wide range of biotech IPCs, ranging from recombinant DNA techniques to traditional bioremediation techniques. In this paper, the classifications were grouped into different biotech areas based on Graff's (2002) classification and on consultations with researchers in the biological sciences. Some 14 fields or areas of biotechnological knowledge were determined (see Table A1).

Table A1
Bioechnological Class Groups.

Class groups	Biotech knowledge field	International patent classification
1	Processes for modifying genotypes	A01H 1/00
2	Tissue culture	A01H 4
3	Medicinal preparations	A61K 38, A61K 39, A61K 48, C07G 11, C07G 13, C07G 15
4	Bioremediation	C02F 3/34
5	Peptides (MABs)	C07K 4, C07K 14, C07K 16, C07K 17, C07K 19
6	Apparatus for enzymology or microbiology	C12M
7	Micro-organisms	C12N 1, C12N 3, C12N 7, C12R1
8	Cell lines and tissues	C12N 5, 00,02,04,10,12,14; C12N15/02-05
9	Enzymes	C12N 9/00; C12N11/00
10	General genetic engineering	C12N 15/00,09, 10,11,63-69,87,70,72-87
11	Genes encoding proteins	C12N 15/29-51
12	Genes encoding enzymes	C12N 15/52-62
13	Bioprocessing	C12P, C12S
14	Micro-biologic measuring and tests	C12Q, G01N

Source: Elaboration based on Graff (2002) and consultations with key informants in the context of project PICT 1833 "*Potencialidades de la biotecnología para el desarrollo industrial en Argentina* [The potential of biotech for industrial development in Argentina]".

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