

Building a bridge: social networks and technological regimes in biotechnology and software

Isabel Salavisa
Margarida Fontes
Cristina Sousa
Pedro Videira

2011

WP n.º 2011/17

DOCUMENTO DE TRABALHO

WORKING PAPER



Building a bridge: social networks and technological regimes in biotechnology and software¹

Isabel Salavisa*
Margarida Fontes**
Cristina Sousa***
Pedro Videira****

WP n.º 2011/17

1. INTRODUCTION	4
2. THEORETICAL BACKGROUND.....	7
2.1 Social networks and technological entrepreneurship.....	7
2.2 Technological regimes.....	12
3. CONCEPTUAL APPROACH TO USING TECHNOLOGICAL REGIMES AS AN EXPLANATORY DEVICE TO NETWORKING BEHAVIOUR	19
3.1 Exploring variety in technological regimes	19
3.2 Defining and operationalizing the properties of technological regimes at firm level	22
3.3 An analytical model: some contributions	29
4. METHODOLOGY	30
4.1 Empirical setting.....	30
4.2 Data collection.....	32

¹ This paper draws on research conducted within the ENTSOCNET project - Entrepreneurs' social networks and knowledge access: The case of biotechnology and IT sectors in Portugal - funded by FCT – Fundação para a Ciência e a Tecnologia (POCI/ESC/60500/2004) and carried out by a team from DINAMIA – Research Centre on Socioeconomic Change, ISCTE-IUL, Lisbon and from LNEG – Laboratório Nacional de Energia e Geologia, Lisbon. The results will be published in a book edited by I. Salavisa and M. Fontes, "Social Networks, Innovation and the Knowledge Economy" (forthcoming). An earlier version of this paper was presented at the 13th Conference of the International Joseph A. Schumpeter Society on "Innovation, organization, sustainability and crises", in Aalborg, Denmark, on 21-24 June 2010.

* DINÂMIA'CET-IUL and Instituto Universitário de Lisboa (ISCTE-IUL), Lisbon.

** LNEG/ UMOSE and DINÂMIA'CET-IUL, Lisbon.

*** DINÂMIA'CET-IUL and Instituto Universitário de Lisboa (ISCTE-IUL), Lisbon.

**** DINÂMIA'CET-IUL, Lisbon.

4.3 Network reconstruction and analysis	33
5. A MICRO-LEVEL APPROACH TO BUILDING TECHNOLOGICAL REGIMES	36
5.1 Operationalization of regime properties	36
5.2 Identifying firm-based technological regimes – a cluster analysis.....	37
5.3 Network configurations.....	39
6. INFLUENCE OF TECHNOLOGICAL REGIMES ON KNOWLEDGE NETWORKS	40
6.1 Definition of the models	40
6.2 Econometric results.....	43
7. DISCUSSION	46
8. CONCLUSIONS	49
REFERENCES	51

Building a bridge: social networks and technological regimes in biotechnology and software

Abstract

The paper investigates the influence of technological regimes on the composition and structure of firms' knowledge networks. We combine insights from two hitherto unconnected bodies of research: one relating technological regimes with the nature of knowledge; and the other relating knowledge and types of innovation with network configuration. Drawing on this framework, we build a number of propositions on the relationship between firms' networking behaviour and the regime under which they operate, operationalized at both sector and firm-level.

These propositions are explored through empirical research comparing firms operating in two distinct knowledge-intensive sectors, namely biotechnology, which is commonly considered more science-based, and software, thought of as mostly technology-based.

As expected, we found that distinct technological regimes affect the knowledge search/exchange process, and thus have an impact upon the network building strategies of the firms.

The results also reveal that sector-based technological regimes have a greater explanatory capacity than firm-based regimes that cross sectoral boundaries.

The use of different approaches and techniques, together with the combination of sector and firm level analyses, provided a tool that enabled a deeper understanding of the variety of networking behaviours among knowledge-intensive firms.

1. INTRODUCTION

In knowledge-intensive sectors, where knowledge is complex and distributed, young, small specialized firms will tend to resort more or less extensively to external organizations to obtain scientific and technological knowledge, as well as other resources necessary to produce and commercialize their products and services. The need to gain access to external resources and competences leads firms to mobilize a set of relationships that can facilitate such access. Research on social networks can therefore provide an important contribution to the understanding of these processes.

The role of social networks in the access and mobilization of resources by firms has been extensively addressed by the literature in recent years (Ozman, 2009). But there has been limited research on the mechanisms and strategies that shape the configurations of these networks, namely on the sources of network diversity among knowledge-intensive firms.

This paper addresses the networking strategies of firms from two different sectors and its objective is, exactly, to understand whether there is heterogeneity in the networks built by firms for accessing resources necessary for innovation and whether such heterogeneity can be associated to differences in the technological regimes under which these firms are operating.

To address these questions we combine insights mainly from two streams of literature: social networks and technological regimes.

Technological regimes are defined as combinations of technological opportunity conditions, appropriability conditions, cumulativeness of learning and the nature of the knowledge base (Dosi, 1988). They constitute the competitive environment for the creation of innovation by firms influencing its configuration and dynamics. But doing so, they also influence the strategies deployed by firms to access different types of knowledge and other resources, to appropriate innovation rents and to design technological strategies. This means that they do not only affect firms' behaviour regarding the development and use of technology and the production of innovation, they also affect their positioning in the market and their relation to competitors (incumbent or potential), customers, suppliers and partners (Malerba and Orsenigo, 1993).

In a way, this has been extensively studied since Pavitt (1984), using broad categories to describe multifaceted patterns of firms' behaviour in their innovative endeavour. However, bridges between technological regimes and the whole behaviour of firms is still relatively scarce (Souitaris, 2002). In a knowledge-intensive world, small firms have to be extroverted agents,

establishing connections of various sorts. This means they have to accede, establish, maintain and develop networks of different types and for different purposes.

The role of networks in the process of firm formation and growth has been object of extensive research, which has namely addressed the functions played by those networks on resource access and mobilization (Elfring and Hulsink, 2003). According to the social networks literature, the formal and informal networks established by the entrepreneurs and/or their firms influence firms' ability to interact with the environment in the search for key resources, but are in turn influenced by the nature of that environment (Ozman, 2009).

Our argument is that some features of the technological environment where firms operate will affect the type(s) of resources searched, their nature and the conditions for their access and, therefore, are likely to influence firms' network building strategies, with impact the structure and composition of their networks. Thus, our main research question is whether the heterogeneity of the networks used by firms for accessing knowledge can be associated to differences in the technological regimes that characterize the sectors in which they are embedded.

The literature has already recognized that there is a relationship between the structure of the knowledge of a sector and the types of network that emerge (Malerba, 2006). However, most empirical research has focused on scientific and/or technological knowledge networks and on formal relationships. We expect to add to this research by also including in our analysis informal/personal relationships, as well as a large variety of technological collaborations.

For this purpose, we have selected two groups of firms created between 1998 and 2008 and operating in two different areas: biotechnology (molecular biology) and software for mobile telecommunications, that, despite being both knowledge-intensive, are likely to have significant differences in terms of their knowledge base (the former being science-based and the latter being primarily technology-based) (McKelvey, 2005; Giarratana, 2004). Indeed, these two groups of firms are part of broader sectors (biotechnology and software) that the literature has long recognized to be characterized by different technological regimes (Malerba and Orsenigo, 1993).

Data about firms' networks (formal and informal) was collected using a combination of complementary methods, involving both search for documentary information (on formal technological and commercial partnerships and on patents); and in-depth face-to-face interviews with the founders, that enabled the collection of information on the entrepreneurs' personal

network and its importance for firms' access to resources necessary for innovation, as well as on the firms' activities, strategies and formal relationships. The data on the entrepreneurs' personal networks permitted us to include in the network the informal ties they mobilize to access different resources for their firms. Since this information is not easily obtained, it is seldom used in innovation studies.

Starting from the firm level networks (re)constructed on the basis of this data, we build six different social networks that capture the set of relationships (formal, informal and global) of the firms from each sector. The global network was obtained through the aggregation of the other two.

Finally, we analyze and compare some dimensions of these networks – e.g. actors' composition, tie nature and content and network structure - in light of some known properties of the technological regimes that characterize the two sectors. The objective is to investigate whether there are differences between sectors regarding the type of networks that are built to access and exchange knowledge, as well as regarding the aggregated networks that emerge as a result of their external relationships; and to examine along which dimensions such differences may be more evident.

The results of this analysis allow a better understanding of the relationship between the nature of the technological regimes and the mechanisms and strategies underlying network building by the firms.

The structure of the paper is as follows: after a theoretical discussion about the role of social networks in knowledge access and innovation and about technological regimes (section 2), we will present our argument and research approach (section 3). The empirical research will be addressed in the remaining sections. In section 4, we present the sample, describe the data collection methodology, present the network reconstruction methodology and analyse and compare firms' knowledge networks. In section 5, we explore the possibility of identifying technological regimes that are not necessarily delimited by sectoral boundaries. In section 6, we investigate the impact of two alternative configurations of technological regimes – sector-based and sector-independent - on the importance, composition and structure of innovation networks and on the positioning of each firm in the sectoral knowledge network. Finally, in sections 7 and 8, we discuss the results and draw some conclusions.

2. THEORETICAL BACKGROUND

2.1 Social networks and technological entrepreneurship

2.1.1 The role of social networks on knowledge access and innovation

Young knowledge-intensive firms, operating in fast changing fields derive their competitiveness from their capacity to quickly expand and renew their knowledge base, in order to generate a steady stream of innovations (Liebeskind et al, 1996; Yli-Renko et al, 2001). Given the frequently complex and distributed nature of the knowledge required for innovation and given their inevitable resource limitations, these firms often end up being strongly reliant on scientific and technological knowledge originating from external sources (Baum et al, 2000; McMillan et al, 2000). On the other hand, these firms often play an intermediate role in innovation systems, acting as intermediaries between research organizations and the market or as specialized suppliers of intermediary technology inputs (goods or services) to other organizations (Hicks and Hedge, 2005; Fontes, 2005). This particular role implies that they integrate extensive technology and knowledge exchange networks (Autio, 1997). Thus firms will need to establish relationships with a variety of organizations that can act as formal or informal sources of information in relevant knowledge fields and/or as partners in technology-oriented alliances that are critical to access key resources and competences. However, admittance to the networks where knowledge (particularly new knowledge) circulates may be restricted (Zucker et al, 1998; Breschi and Lissoni, 2001). Similarly, the ability of young firms, who have not yet built a reputation, to establish relationships with key actors, may be limited, requiring a previous credibilization (Powell et al, 1996).

Research on social networks has shown that the process of identification and access to key knowledge sources as well as the process of admittance to the circles where such knowledge circulates and where alliances are built relies strongly on networks (Fontes, 2005; Liebeskind et al, 1996; Stuart and Sorenson, 2003; Murray, 2004; Owen-Smith and Powell, 2004). This encompasses both the personal networks built by entrepreneurs along their academic and professional trajectories and the linkages intentionally established with strategic purposes (which are often mediated by the former) (Hite & Hesterly, 2001; Grandi and Grimaldi, 2003).

In fact, recent research has shown the importance of the entrepreneurs' social capital in accessing several tangible and intangible resources needed for the formation and growth of new firms (Greve and Salaff, 2003; Singh, 2000). Entrepreneurship is described as a social process

embedded in social structures and thus being strongly influenced – facilitated or constrained - by the social networks of firms' entrepreneurs (personal networks) and by the social environment in which the process takes place (inter-organizational networks).

These networks permit to circumvent some of the constraints faced by the entrepreneurs facilitating access to relevant resources (Ozman, 2009). Their role is particularly relevant in the case of knowledge intensive firms, given the combination of high levels of uncertainty (both technological and market) and resource constraints that characterize them (Yli-Renko et al, 2001, Johansson, 1998). In addition some authors also argue that knowledge access and exploitation are social processes (Kogut and Zander, 1992) and thus social networks can be crucial at this level, permitting to increase the scope, depth and efficiency of knowledge exchanges (Lane and Lubatkin, 1998; Schrader, 1991). Social network can also contribute to afford scientific (and market) credibility to firms who are developing technologies whose value is not yet fully demonstrated (Moensted, 2007).

Thus, young knowledge-intensive firms are likely to mobilize or develop a set of knowledge-related relationships that can facilitate access to key knowledge sources. But it is important to take into account that, not only the nature of firms' knowledge requirements vary, but the conditions in which knowledge access takes place will differ, being influenced by the knowledge and social environment and by firms' own knowledge endowments (Malerba and Orsenigo, 1993). Therefore, it is to be expected that firms with diverse types of knowledge requirements and originating from and operating on different knowledge environments will build knowledge networks with diverse compositions and structures. However, although the literature has already recognised that there is a relationship between the structure of knowledge of a sector and the types of networks that emerge (Malerba, 2006), the mechanisms and strategies that shape the configurations of these networks, and namely the sources of network diversity, have still been object of limited research.

Previous exploratory research conducted by the authors (Sousa et al, 2011) has found that different network configurations are associated with the access and mobilization of different types of resources and, particularly, that scientific and technological knowledge is accessed through networks that differ significantly from those mobilized to obtain other (non-technological) resources (Sousa et al, 2011). In this paper we focus on the networks established to acquire and exploit this particular resource - knowledge - and attempt to characterise these networks and to gain a better understanding of the conditions that may be behind variety in network configurations at this level. For this purpose we will use the framework and techniques provided by social network analysis.

2.1.2 The analysis of social networks

Social networks can be defined as a set of nodes or actors connected by a social relationship (or tie) of a specified type (Castilla et al., 2000). Network configurations differ according to the type of actors and the type of relations they encompass. Actors may be organizations or individuals. Relations can be characterized by the type of interaction (e.g. formal vs. informal), the intensity of the tie (e.g. strong vs. weak) and its content (i.e. the type of resource(s) that circulate through it), as well as by the relative position of the network actors².

With respect to the structure of networks, one important contribution of the social network literature concerns the distinction between strong and weak ties and their respective effects on the process of resource mobilization. According to Granovetter (1973), the strength of ties can be analyzed using a combination of aspects like frequency/duration of the tie, emotional intensity, intimacy and reciprocity. Strong ties are associated with higher levels of social proximity and trust, being favoured by frequent interaction (McEvily e Zaheer, 1999; Johansson, 1998). However, building and maintaining strong ties is costly and thus actors tend to limit their number. Rather, weak ties are looser connections based on more occasional interactions and thus may be established with a wider range of actors.

The balance between strong and weak ties affects the knowledge transfer process (Maskell and Malmberg, 1999) as well as the cost of accessing knowledge (Coleman, 1988). There is some debate over the effects of different configurations, i.e. more densely embedded or “closed” networks with many strong ties (Coleman, 1988), vs. more “open” networks with many weak ties (Granovetter, 1973) and structural holes (Burt, 1992). According to some authors, the former, by generating trust and cooperation between the actors (Ahuja, 2000) are more beneficial: they facilitate the exchange of high quality information (Gulati, 1998; Van Geenhuizen, 2008) and of complex (Hansen, 1999) and tacit knowledge (Lundvall, 1993), and are particularly important to access scarce resources (Lovas and Sorenson, 2008). According to other authors, the latter, by enabling the establishment of relationships with multiple unconnected actors has the advantage of providing access to non-redundant information (Burt, 1992) eventually leading to the identification of opportunities of which competitors are unaware

² Network position is usually measured by network centrality measures, which are described as offering different opportunities to access the relevant sources of resources (Powell et al, 1996). Since our approach was based on an analysis of firm-level networks (i.e. ego-networks with only direct ties and thus where all actors in the network are directly related with the firm) it does not make sense to consider actors' position in the network: our ego firm is always the most central actor and the distance between the ego and all alters is always equal to zero. To consider also indirect ties at this stage of research, we would have required to expand data collection to all alters in the whole network, which was much beyond the scope of this research.

(McEvily and Zaheer, 1999; Low and Abrahamson, 1997). While it is suggested that a mix of strong and weak ties is critical for the development of young firms (Uzzi, 1997), the relative weight of each in firm's network structures is likely to be determined by the nature and objectives of the search process: e.g. exploration vs. exploitation, search for information vs. search for knowledge; nature of knowledge being searched, namely degree of newness, complexity and tacitness (Gilsing and Nooteboom, 2005; Giuliani, 2007; Morrison and Rabellotti, 2009; Ahuja, 2000; Freel and de Jong, 2009).

Another relevant element in the analysis of network structure is the distinction between formal and informal relationships. Knowledge networks are generally composed of both. For instance, Powell and Grodal (2005) describe them as including “formal contractual relations, such as subcontracting relationships, strategic alliances or participation in an industry-wide research consortium, and informal ties, based on common membership in a professional or trade association, or even a looser affiliation with a technological community”. However despite the implicit recognition of the importance of informal knowledge flows in innovation, that is reflected on the extensive literature on spillovers (Jaffe et al., 1993; Autant-Bernard, 2001), research has largely focused on formal inter-organizational (often inter-firm) networks (Hagedoorn 1993; Gulati, 1998; Colombo et al, 2006; Okamura and Vonortas, 2006). Informal networks have been less frequently addressed, and sometimes only as a complement to more formal relationships.

Some authors have nevertheless attempted to gain a more comprehensive understanding of the actual informal knowledge flows that take place between individuals in different organizations. One stream of research used co-patenting / patent citations (Breschi and Lissoni, 2009; Singh, 2005) or co-authorships (Murray, 2002) to identify and investigate the origin and dynamics of knowledge communities that develop outside specific organizational boundaries but are highly influential at firm level. Research on “communities of practice” (Wenger, 1998; Rosenkopf and Tushman, 1998) and epistemic communities (Steinmueller, 2000) has also offered some insights into the nature of these interactions. However, only more recently have researchers started to address directly the exchange processes that take place at the micro-level, conducting purposive data collection on the actual interactions between individuals. Following the seminal work of Von-Hippel (1987), these authors have traced the informal know-how trading activities that occur among firm employees and/or among firms entrepreneurs (who often are also researchers/technicians), or between firm employees and university researchers (Kreiner and Schultz, 1993; Lissoni, 2001; Giuliani and Bell, 2005; Dahl and Pedersen, 2004; Schrader,

1991; Morrison and Rabellotti, 2009; Trippi et al, 2009; Ostergaard, 2009) and investigated the purpose, contents and structure of the associated flows.

According to Cassi and Morrison (2007) one important contribution of these studies was to put the focus on the “identification of the relevant community of actors and the relevant type of knowledge”, enabling a better understanding of the configuration of these informal knowledge networks.

While research tends to focus either on formal or on informal networks, they are strongly intertwined. Underlying formal agreements there is frequently a variety of informal (social) relations (Powell et al., 1996), which can that have an important contribution to their success (Kreiner and Schultz, 1993). Informal relations may have emerged as a result of interactions in the context of the formal collaboration, or may be based on pre-existing personal relationships that were mobilized to sustain or complement the formal activities or even be behind their establishment. In spite of this, formal and informal networks will only partially overlap since they may have been established with different purposes, encompassing different types of actors and evolving along diverse time spans (Kratzer et al., 2009). Thus, firms’ relationships may encompass a dense web of ties, both formal and informal and it is relevant to consider their combined action and assess the effective contribution of both.

2.1.3 Networks and the nature of knowledge

In summary, when addressing the configuration of firms’ knowledge networks it is possible to conclude that the actor composition of these networks reflects the type of knowledge sources and partners used by firms during the process of knowledge production and exploitation, providing an indication of the relative relevance of different types of organizations in this process. Similarly, it is possible to suggest that the structure of these networks - in this case the mix of formal and informal relationships and the relative importance of strong and weak ties – reflects the nature of the channels used by firms to access and exchange knowledge and can provide some indications regarding the nature of the flows that take place, either globally or with some particular types of actors.

Going back to our previous argument regarding the potential differences in terms of firms’ knowledge requirements and endowments and in terms of the characteristics of the context where knowledge exchanges take place, it is possible to advance that the composition and structure of the firms networks will reflect, to a great extent, the nature of the knowledge firms are exploiting (namely the nature of their knowledge base) and the nature of the knowledge

environment it induces. In other words, it is possible to suggest that the differences in the composition and structure of firms' networks reflect – and therefore can be at least partly explained by – the differences in technological regimes that are implied by the nature of the knowledge (Malerba and Orsenigo, 1993).

Thus, the technological regime framework can be used as one useful analytical device to investigate the sources of variety in firms networking behaviour. Although we are aware that the factors that influence firms' strategic behaviour go beyond “technological imperatives”, it can be argued that in technology intensive sectors – such as biotechnology and software – the nature of knowledge being exploited and namely its impact on the conditions in which knowledge is produced, disseminated and accessed are likely to be an important determinant of firm's networking behaviour.

2.2 Technological regimes

2.2.1 Origin and evolution

Since Schumpeter, the concern on the conditions for innovation by firms is central as well as is central the diversity of forms taken by the innovative processes. Since Schumpeter's Mark I and II models, Schumpeterian hypotheses on the influence of firms' size and market concentration on the innovative performance have been extensively adopted, discussed, criticized and empirically tested.

Technological regimes are ways of representing the technological environments – and their diversity - of the firms. The concept of technological regimes allows to “organizing” the notion of technological environment that exerts a strong influence on the behaviour of firms. It adds both simplicity and complexity to that basic notion: simplicity, because it reduces the potential multiplicity of possible technological environments to a few fundamental types; complexity and deeper understanding, because it sheds light on the fundamental properties that emerge from and simultaneously mould the environment and its influence on firms' behaviour.

Main properties of the environment are represented by the main dimensions of technological regimes - technological opportunity conditions, appropriability conditions, cumulativeness of learning and the nature of the knowledge base (Dosi, 1988). It is according to the specific and evolving configuration of these dimensions that firms develop their innovative activities. The original ideas by Dosi were later on clarified and developed by Malerba and Orsenigo (1993).

Since technology is basically knowledge about economic activities, and furthermore increasingly relying upon scientific knowledge, analogies are likely to exist between the development processes of science and of technology. In fact, both processes are strongly informed by fundamental discoveries that induce sharp ruptures, which are followed by periods of cumulativeness along a pre-defined path. The Kuhnian approach to scientific progress has proved to be a major source of inspiration to understand technological development, as Dosi has discovered and proposed in the early 1980s (Dosi, 1982). Cumulativeness (as opposed to rupture) is then a major trait of normal science development and of most technological innovations (incremental).

Technological opportunity means essentially the ease of innovating for a given investment in search for new solutions (Malerba and Orsenigo, 1993). Opportunities have long been a major point for the understanding of entrepreneurship endeavours. But in management approaches these opportunities are mostly market opportunities that are supposed to be “found” by the entrepreneur (see Shane, 2003, for a survey). In neo-Schumpeterian approaches, opportunities are built by the entrepreneur who innovates. However, once a new technological field is open it offers high technological opportunities that are rewarding in terms of high profit perspectives. This is particularly true when the technology is radically new, permits very pervasive applications and has a high potential to develop and transform itself, since it entails a very strong potential for the creation of a great number of new or significantly improved products and processes, over an extended span of time.

Appropriability conditions are crucial for technological creation, due to the knowledge nature of technology. Unlike common markets, technology transactions face a problem of property recognition and use. This is due to the quasi-public nature of technological knowledge that calls for specific institutions and firms’ strategies to secure exclusivity of use to its creators, at least over a long enough period to be compensated for the innovative efforts.

Finally, the nature of the knowledge base: knowledge can rely more or less on cutting-edge scientific advances; be more or less complex; be more or less dependent from external sources, such as universities and the like; be more or less tacit. This dimension is obviously strongly related to the other three dimensions that stand as the main characteristics of the innovative activities according to the technological regimes approach.

From a very different perspective, Pavitt (1984) has contributed in a fundamental way to the understanding of technological environment. Drawing on the notion of technological trajectories presented in subsequent research (by Dosi, Nelson and Winter, Freeman, Rosenberg, Gold,

Sahal and others) and based on empirical data on significant innovations and on innovating companies in British manufacturing, he built a sectoral taxonomy made of four broad categories corresponding to the multifaceted patterns of firms' innovative activities. Each category encompassed a group of sectors, assembled according to the sectoral sources of technology used in the sector; the institutional sources and nature of the technology produced in the sector; and the characteristics of innovating firms, such as size and principal activity (Pavitt, 1984: 346). The author identified four categories or groups of sectors, labelled as supplier-dominated sectors; production-intensive sectors (subdivided into specialized suppliers and scale-intensive sectors) and science-based sectors. By doing so, he has proceeded to a dramatic clarification and reduction of information regarding the multiplicity of ways innovation takes place. Since his influential article, it has been admitted that firms' innovative profile can be ascribed to a main pattern within a set of patterns.

Drawing on Pavitt's major contribution, further research has deepened and enlarged the taxonomical work on innovation, to account for the specificity of services or to adapt the original categories to specific purposes, subjects and research questions. This is the case with the addition of a fifth innovation pattern – labelled as “information intensive” – to describe innovation processes in services, especially in finance, retailing, publishing, telecommunications and travel. This extension in fact was done by Pavitt himself even if with other authors (Tidd et al, 1997).

Other authors have used different categories or regimes. This is the case of Marsili (2002) who proposed a typology to identify the technological dimensions that mostly affect entry into a sector. The typology was built according to the characteristics of technological opportunities and of the nature of knowledge in industrial sectors and encompassed five regimes: the science-based regime; the fundamental-processes; the complex (knowledge) system; the product-engineering and the continuous-processes regime. This typology was also adopted in a study on the relation between technology and industrial structures and dynamics in Dutch manufacturing (Marsili and Verspagen, 2002). Interestingly, and more recently, the same author has contributed to a taxonomical exercise that turned out to identify basically the same categories as Pavitt (1984) had done twenty years before, using a totally different data basis and a different set of variables (science-based, specialized suppliers, supplier-dominated and resource-intensive). The purpose was to study the innovative activities and correlated business practices and strategies of small – and even micro-innovative firms in Dutch manufacturing and services (de Jong and Marsili, 2006).

Services have deserved a specific attention, being quite unlikely that a unique innovative pattern could account for all innovation processes in such a heterogeneous reality. In the same line, Evangelista (2000) has drawn from the well-known heterogeneity of these activities to look for the identification of innovative patterns within the services industries in Italy. The taxonomical exercise produced four groups of sectors: technology users; S&T-based; interactive and IT based; and technical consultancy, in fact a combination of the two latter groups.

2.2.2 The evolution of technological regimes

Technological regimes are dynamic entities as we can conclude from the previous section. But their metamorphoses could be ascribed either to theoretical refinements or to factual historical reasons, or both. The point here is to introduce a time component in the analysis, enabling us to address the following questions. First, is there an ideal type of technological regime in each long phase of technological development or to put in other terms is there a correspondence between the typical dominant technological regime and the specific broad stage of capitalism? And if so, second, is it possible to identify the traits of a distinct technological regime that corresponds to the present stage? According to Archibugi (2001), the answer to the first question is affirmative.

In fact, when proceeding to a critical assessment of Pavitt's taxonomy sixteen years on, Archibugi raised the question of "how can this taxonomy help us to understand economic evolution" (2001: 422). He then wrote that it can be read dynamically in two different ways: predicting the most likely developments along current technological trajectories of firms; and suggesting a kind of new dominant way of innovative activities in each stage.

Adopting a long waves' approach of economic development, Archibugi writes that the emergence of specialized suppliers as a distinctive category of firms took place as a separation from supplier-dominated firms, in the transition from the first long wave to the second one. Likewise, "scientific discoveries in the field of chemistry and electricity opened up new business opportunities which were quickly exploited by a generation of new firms" (2001: 423). Science-based firms would then have been created with the third long wave, in the turn of the 19th century. The next wave, labelled as Fordism, was based on mass production, new complex products, large firms and efficiency improvement and scale exploitation strategies ("cost-cut trajectories"), corresponding to the scale-intensive category. At the moment he writes, the so-called New Economy stage, the author argues that a generation of information-intensive firms were rising, in manufacturing and services industries and "based on the intensive analysis and use of data-processing" (2001: 423). At this stage, and in a sketch form, the industrial organization would be characterized by networks of firms and strong user-producer interactions.

We are not going to explore this subject now. Suffice here to say that it seems consistent that innovative activities by firms have undergone huge transformations in the current techno-economic paradigm. In fact, alongside with an increase in the complexity and specialization of knowledge creation activities, innovative activities have become more dependent on scientific knowledge; firms have become more specialized; and collaborative practices have gained an accrued importance. The incidence of these phenomena on the configuration of technological regimes is yet to be assessed.

2.2.3 Inter-sectoral and intra-sectoral diversity of technological regimes: The cases of biotechnology and software

Following along the path opened up by Pavitt, a number of authors have studied the inter-sectoral diversity of innovative activities using the analytical framework of technological regimes. A relevant paper was the one by Malerba and Orsenigo, in 1993. According to the link between the nature of technological regimes and the type of firm behaviour, they examined the histories of three relevant technology-intensive industries: the semiconductor industry, biotechnology, computer hardware and software. From a different perspective, Malerba examines the variability of innovation across sectors in subsequent papers (see Malerba, 2005). Within a diverse theoretical framework and with different aims, other papers have compared innovative processes, organizational modes in modern biotechnology and software or computing services (McKelvey, 2005; Swann and Prevezer, 1996; Weterings and Ponds, 2009).

A large number of studies focusing on one of the sectors also provide very relevant contributions to the understanding of innovation processes and their conditions and as such will be also used in the brief characterization and comparison that follows.

Biotechnology is the most common example of a science-based or science-driven sector. In fact, modern biotechnology emerged as a result of major scientific breakthroughs in the 1970s: recombinant DNA and hybridoma technology. This young sector owes its very existence to the new technological and commercial possibilities opened up by those fundamental discoveries. Some authors claim that biotech is not an industry but rather a set of technologies (McKelvey, 2005). But since it consists of a large spectrum of scientific and technological activities with a wide application across industries, it can be labelled as a quasi-sector.

Within the biotechnology sector several distinct types or groups of firms coexist. A first group is made of companies that try to commercialize products as soon as possible, often adopting a niche strategy. It includes companies dedicated to the production of diagnostics kits based on

the hybridoma technology, among others that also develop specialized applications. A second group encompasses companies that focus on the creation of knowledge through intensive research activities, and whose aim is patenting and licensing to other firms from several industries such as pharmaceuticals, agro industry and chemicals. Firms in the second group are highly based on cutting-edge scientific advances in genetic engineering (recombinant DNA) and strongly connected with pharmaceutical companies. The two groups are usually academic spin-offs that maintain a close relationship with the academy (Malerba and Orsenigo, 1993). For both groups appropriability of their knowledge creation outcomes is critical.

Established pharmaceutical companies have developed diversified strategies to deal with the emergence of molecular biology in the 1980s. A dominant trait in these strategies is that they could not afford ignoring what was happening in the world of new small biotech firms. They had then to build collaborative relations with them, while acquiring new competencies and transforming the content of their intra-firm R&D activities. As Malerba writes: “division of labour has taken place between new biotechnology firms (NBF) which lacked experience in clinical testing and established companies that (with time) adopted molecular biology. Networks of collaborative relations (facilitated by the science base and by the abstract and codified nature of knowledge generated by NBF) emerged in the sector”. (Malerba, 2005:70). As knowledge has become more tacit, vertical integration gained relevance. Mergers and acquisitions were quick forms to achieve that integration (Malerba and Orsenigo, 1993). However, as the small firms’ world continued to expand – relying on the very fast rate of scientific creation in the field – collaboration between large and small firms went on, including universities, other public and private research organizations, venture capital companies and individuals.

A striking feature in what has been written is that in biotech small firms two different patterns have emerged: a more science-based pattern and a more application-oriented one. Malerba and Orsenigo had already pointed out that “in the absence of products generating revenues, the NBF became essentially research companies and specialized suppliers of high technology intermediate products, performing contract research for and in collaboration with established companies” (1993: 55). The split between the two types of activities seems to have consolidated over the years, with some companies becoming research companies and the others becoming specialized application-oriented. The former had a strong focus on basic research and got funded by venture capital, at first, and later on obtained their revenues through research contracts on behalf of large established pharmaceutical companies or through patent licensing. It is what Coriat et al (2003) have labelled as the “science-based type ‘2’ model”.

As to the software sector, the characterization of its dominant technological regime is less clear and consensual. Some authors have ascribed it to the specialized supplier category (de Jong and Marsili, 2006) while others have labelled it simply as information-intensive (Tidd et al, 1997), what appears as a simplification. Since business models have here a strong interaction with innovation processes, it is likely to happen an inner differentiation regarding technological regimes, a dominant specialized supplier coexisting with a more complex knowledge based one, with similarities with the science-based regime. In fact, it is a much segmented industry, encompassing three main segments: operating systems, applications and middleware. A particular segment is embedded software, which permanently integrates a particular hardware unit. Its main customers include the telecommunications industry, the mobile phone industry, the automobile industry, consumer electronics producers, medical equipment producers and robotics makers (Lippoldt and Stryszowski, 2009).

Provisionally, we may define software as a technology-intensive sector relying on a complex and diversified knowledge base, but where tacitness appears as much more relevant than in most biotechnology activities. Furthermore, it does not rely upon scientific advances, to the same extent as it does in biotechnology, and even less upon scientific breakthroughs. In short, we are not dealing with a science-based sector as a whole. This does not mean that relations with universities are unimportant, but the form, content and purpose of those relations is different: they tend to be informal and, although the access to academic knowledge is relevant, more relevant seems to be the access to talented highly skilled engineers in order to continually improve the skills base of the companies (Giarratana, 2004). The level of technological opportunities is still high but mostly depending on the user-producer relationships, especially when it comes to embedded software and applications, where customers are also drivers of technological innovation in the software industry. Likewise, the perceived clients needs, actual and anticipated, induce packaged software firms to innovate in problem-solving solutions. Furthermore, opportunities are reinforced by the enormous (almost universal) pervasiveness of software applications. The modularity of software programming makes it a process of high cumulateness. Finally, the question of appropriability – very affected by the open source software movement (see Malerba, 2005 and McKelvey, 2005) - relies much less in patenting (at least in Europe) than in other forms of property protection, like standards, copy rights enforcement, techno-commercial strategies such as lead-time and proliferation of products strategies (Giarratana, 2004) and partnerships and alliances both among software firms and with large customers from different sectors (computer producers, telecommunications equipment producers and services providers, consumer electronics, finance, business services, distribution,

defence and aeronautical industries, and public services of general interest). Cooperation among firms and networking is quite relevant here (Malerba and Orsenigo, 1993; Salavisa et al, 2009).

From what has been written, we may conclude that biotechnology and software sectors present sharp differences regarding their dominant technological regimes, although both belong to a broad category of technology-intensive sectors. However, it has become also clear that in both an inner differentiation exists, inviting us to conduct an analysis that goes beyond the sectoral boundaries. This is the “démarche” followed in studies that tried to identify technological regimes drawing directly on firms data (de Jong and Marsili, 2006; Leiponen and Drejer, 2007; Peneder, 2010).

3. CONCEPTUAL APPROACH TO USING TECHNOLOGICAL REGIMES AS AN EXPLANATORY DEVICE TO NETWORKING BEHAVIOUR

3.1 Exploring variety in technological regimes

The rationale behind the definition of a “technological regime” is that the nature of the knowledge underlying the technologies that firms develop/use, will, to an important extent, shape and constrain firms’ innovative behaviour – i.e., their strategies, forms of organization and type of relationships, namely those concerned with gaining access to and transmitting knowledge (Malerba and Orsenigo, 1997). Thus, it is expected that different technological regimes, which reflect the diverse nature of the knowledge being exploited, will contribute to explain differences in firms innovation networking behaviour, as expressed through the role, composition and structure of the knowledge relationships they establish.

In order to address this question, we start by assuming that, while both biotechnology and software are knowledge-intensive sectors, the nature of knowledge being developed and used by firms in both sectors is diverse and therefore firms are likely to operate under different technological regimes. This assumption is sustained by the literature reviewed on the previous section.

However, as was also pointed out above, the assumption of sectoral homogeneity of innovative behaviour has been questioned by some authors. The objections were raised at two main levels. Some authors criticized the “technological determinism” that underlies the close association between technological regimes and innovative behaviour, arguing that it ignores the potential for variety that derives from firms different strategic responses to substantially similar conditions (given bounded rationality of the agents). They argue firms’ innovative behaviour

effectively results from the interplay between technological imperatives that induce some regularities in the way firms organize their innovation activities and the firm-specific decisions regarding the strategic conduction of these activities which result from local search and are likely to generate diversity (Leiponen and Dredjer, 2007; Nesta and Dibiaggio, 2003).

Other authors questioned the close association between sectors and technologies. The relationships between technological regimes and sectoral patterns of behaviour is based on the assumption that sector-based firms are involved in the development / use of similar technologies and thus operate under a relatively homogeneous technological environment. However, this is not necessarily the case. On the one hand, industries or sectors are often defined according to the product they supply and not the technology they use (Peneder, 2010). On the other hand, industries and sectors are often too broadly defined thus encompassing segments that are likely to use quite different technologies. Thus, even only taking into consideration the influence of the technological regime upon firms' behaviour (and thus disregarding the potential diversity of firms' responses to it), there is scope for within-industry variety. This variety may be masked by the practice of using aggregate data for measuring the properties of technological regime at industry level, which results on the identification of average behaviours (Peneder, 2010).

Recent research has been conducted with the purpose to address this question, based on industry-wide data sets and relying on the technological regime framework (Leiponen and Dredjer, 2007; Peneder, 2010). It has been concluded that although regularities can be found in terms of innovative behaviour, these do not necessarily take place within industries. Rather, there is also within-industry variety and across industry regularities.

The notion of intra-regime variety has also been addressed by some authors. These authors have basically focused on industries characterized by fast technological change (usually biotechnology), addressing the particular case of a broadly defined "science-based regime", which is particularly relevant for our discussion.

For instance, Nesta and Dibiaggio (2003) have looked in detail into the sources of firms technological differentiation within an industry characterized by a science-based technological regime. While accepting that firms differ at the level of organizational structures and competencies, they consider that differences in the knowledge base are also sources of heterogeneity. They argue that firms may differ at this level for two reasons: because they develop competencies in different technologies (heterogeneity will be based on asymmetries in knowledge endowments); or because of the ways they use technological knowledge that is

generally available to the firms in the industry (heterogeneity is based on their specific exploitation of bodies of knowledge).

Orsenigo et al (2001) discussion on biotechnology in pharmaceuticals provides some additional insights into this type of variety. It illustrates the fact that even when exploiting a seemingly homogeneous technology, firms will adopt different strategies/positioning: exploring new trajectories for incumbents (as highly specialized suppliers) in cases of application specific (co-specialized) technologies; with more autonomous product or service based strategies in the case of generic (transversal) technologies.

Coriat et al (2003) also addressed this question arguing that there are two main sources of differentiation within science-based regimes. One is the nature of relations between academic research and industry, i.e. the level of contribution of science academic research and type of channels firms use to source knowledge from academic research (ranging from scientific links through publications and conferences, to contractual relations, to informal contacts and exchange of personnel). The other is the conditions of appropriability – i.e. the impact of patents on firm's strategies and the differences in motives for patenting (patents as sources of revenues or for signalling competences vs. patents as basis for negotiation).

It is also interesting to take into account Malerba (2005) analysis of “pharmaceuticals and biotechnology” and “software” sectoral systems, conducted in the context of his examination of five broad sectors where technological change is rapid and innovation plays a major role. His discussion of the behaviour and dynamics of these broad sectors highlights the presence of particular behaviour in specific segments and the changes that are taking place in some of them, which may generate additional variety not reflected in previous studies.

On the whole, these streams of research suggested that we questioned the assumption of complete overlap between sector and regime in the cases of biotechnology and of software. This option required us to go back to the definition of technological regime and to attempt to uncover the actual regimes under which the firms analysed operated, given the nature of the technologies they were exploiting. According to the lines of reasoning underlying those streams of research these might be more effective in describing the structural conditions faced by the firms thus would have a better explanatory power regarding their innovative behaviour and thus regarding one element of that behaviour – the networking strategy.

For this purpose it might be useful to return to the early definition and discussion of technological regimes conducted by Malerba and Orsenigo (1993), where they examine the

specific opportunities and problems derived from different combinations of these basic properties of technology, as well their outcome in terms of the “menu” of viable basic technology strategies and modes of organization available to firms. Along these lines, our approach was to examine how the particular combination of the basic properties of the technologies these firms are exploiting effectively impacted their innovative behaviour. Our objective is to understand whether we can identify regularities in the patterns of behaviour they generate and whether these regularities basically develop along the sectoral boundaries or rather across these boundaries.

As was the case with other researchers who were investigating the presence of within-industry variety, we opted for conducting the analysis at the level of individual firms, using micro-data (collected through interviews) to operationalize the properties of regimes. While this type of data is expected to enable a greater adherence to the conditions faced by firms, it also has the disadvantage of providing only indirect measures – that is, in practice it measures the (expected) effect of these properties of knowledge on the behaviour of firms³.

3.2 Defining and operationalizing the properties of technological regimes at firm level

The operationalization of the properties of the technological regimes is not always straightforward (Castellaci, 2007; Leiponen and Dredjer, 2007) and researchers frequently rely on indicators that are only rough proxies for the complex conditions that are being investigated and their combined effects, which cannot always be measured directly. These difficulties are magnified when attempting to achieve this operationalization at firm level (as opposed to the aggregated level), since what can effectively be observed, in most cases, is the influence of these properties on firms’ innovative behaviour, as was already pointed out above. Having in mind this limitation, we still regard this approach as worth pursuing since only firm level data will enable us to assess eventual regime regularities that go beyond the sectoral level of aggregation.

For this purpose, we will draw on contributions from research conducted at industry/ sector level, which have attempted to measure some dimensions of technological regimes using firm level indicators: e.g. the Yale survey in the US (Levin et al, 1987; Klevorick et al, 1995; Cohen et al, 2000), the PACE survey in Europe (Breschi et al., 2000; Arundel et al, 1995) and more recently some attempts to measurement based on data from the Community Innovation Survey (CIS) (e.g. Frenz and Prevezer, 2010; Evangelista and Mastrostefano, 2006; Marsili and

³ This is nevertheless the case with most indicators used to operationalize the properties of technological regimes.

Verspagen, 2002; Peneder, 2010, Castellaci, 2007). A few authors have also conducted purposeful surveys targeting more specific populations (e.g. de Jong and Marsili, 2006; Palmberg, 2001).

When attempting to measure key features of the technological regimes underlying the innovative activities of the firms being studied we will focus on two key properties – technological opportunities and appropriability. The characteristics of the knowledge base – namely pervasiveness and tacitness - will also be taken into account, but will be addressed through the impact they have on the nature of opportunities and on the appropriability conditions.

3.2.1 Technological opportunity

Technological opportunity is defined as the ease of innovating for a given investment in search for new solutions (Malerba and Orsenigo, 1993). While this definition focuses essentially on the level of opportunity, Malerba and Orsenigo (1997) also stress two other dimensions that are relevant to characterize technological opportunity: its sources and its degree of pervasiveness⁴.

The level of opportunity is the most commonly used dimension. Since the objective is to assess the ease of producing innovative output relatively to the amount of resources devoted to innovative activities, it is usually measured in terms of intensity of R&D efforts (R&D expenditure as a share of sales or R&D employment as share of total employment). It is also possible to differentiate between research in basic science and in applied science and assess the presence and relative importance of efforts devoted to both (Breschi et al., 2000).

The distinction between basic research (which tends to be associated with the production of more generic knowledge) and applied research (associated with the production of more specific knowledge) (Breschi et al, 2000), is also pertinent when it comes to assess pervasiveness. Pervasiveness can be defined as the possibility of using the same core knowledge in a variety of applications (Malerba and Orsenigo, 1997), which, at firm level, can be equated to a greater or lesser ability for diversifying into a variety of markets or for generating a continuous stream of new product generations. The more generic is the knowledge the greater the scope for applications and the higher the possibility of enabling a greater variety of new search

⁴ Pervasiveness (as an outcome of the level of generality of knowledge) as opposed to specificity is equally discussed in the technological regimes literature as a property of the knowledge base. Our interpretation is that this particular property of knowledge has implications for the opportunity conditions faced by the firms and therefore we include it in the definition of the technological opportunity dimension.

trajectories (Saviotti, 1998) and, therefore knowledge that originates from scientific research (particularly from basic research) is more likely to be characterized by a higher pervasiveness (Marsili, 2002).

Pervasiveness is less easy to operationalize, particularly at firm level, which have limited its use in empirical research. However, it is possible to gain some insights into its occurrence by combining information on the nature of the knowledge being exploited – i.e. whether the knowledge is generic thus at least providing the scope for a broader range of applications – with evidence on the actual materialization of these opportunities⁵ – i.e. the presence of technology or product/market diversification.

The sources of technological opportunity also vary depending on the nature of knowledge firms use for innovation. Following Klevorick et al. (1995) it is possible to distinguish between advances in scientific understanding on one hand and technological advances, originating either outside the industry or from R&D activities internal to the industry, on the other hand. The relative importance of these different sources to the pool of technological opportunities in which firms draw will vary and these differences will also be reflected upon the balance between internal and external sources of information and, regarding the latter, upon the type of organizations on which firms rely to access them. In particular, the relevance of academic science is used by these authors as a proxy to the importance of new scientific developments and therefore the extent to which firms rely on research organisations as sources of knowledge can be regarded as an expression of such importance and as an indicator of the presence of the associated type of opportunity conditions⁶. In the particular case of young knowledge-intensive firms, it may also be interesting to consider firms' origin – that is, whether they are academic spin-offs – since it is an additional indicator nature of knowledge being used⁷.

In summary, an analysis of technological opportunity at firm level in the case of young knowledge-intensive companies, will have to take into account the level and contents of R&D

⁵ It should be taken into account that more generic technologies also tend to be more distant from applications and thus it may be more complex to identify such applications or to select from the various alternatives.

⁶ According to Klevorick et al (1995), science can provide different types of contributions: it can add to the broad stock of knowledge on which firms indirectly draw or can provide new scientific developments that directly open new technological opportunities. While most knowledge-intensive firms draw on the former, only some will be able to identify new scientific developments that are relevant to their activities and potentially lead to more radical innovations. In this context, a close link to academic research and the recognition of its importance for firms' activity can be an indicator of high opportunity conditions.

⁷ The importance of knowledge originating from academic research - in particular knowledge originating from new scientific developments that can break with the knowledge base of firms in the industry - may be regarded as providing an indication of low relevance of previously accumulated knowledge (Winter, 1984) and therefore of low cumulateness.

effort, the structure of knowledge sources on which firms draw and – if possible – at least an approximation to the nature of the technological output being produced.

Following previous research it is to be expected that a higher degree of technological opportunity is associated with a higher intensity of R&D effort and a stronger reliance on scientific research, as generator of more generic knowledge and thus of greater potential for pervasiveness .

Biotechnological is generally defined as displaying a great proximity between science and its application, which will, in principle, have implications on the nature of technological opportunity conditions faced by the firms. It is to be expected that scientific knowledge plays a more important role as source of opportunity for innovation for a significant subset of biotechnology firms - although there may be differences among them regarding the relative importance of basic vs. applied science - and that, therefore, they will have more intense relationships with suppliers of this type of knowledge and will also be more likely to start-up as spin-offs from research organizations. However, this general appraisal does not mean that all biotechnology firms will follow this “science-based” model or, conversely, that we cannot find a subset of software companies that also fit into this model.

The differences between biotechnology and software firms may be less clear-cut concerning the absolute level of R&D effort (even if the contents of that effort may vary) and the level of reliance on external sources of knowledge (even if the source organizations may vary). However, it can be expected that the nature of the knowledge introduces some differences on the type of exchange that takes place with external sources. While biotechnology firms rely on scientific knowledge that tends to be more frequently codified, software firms rely more strongly on tacit knowledge and thus they will be relatively more likely to establish informal relationships for knowledge exchange. Finally, while the potentially more generic nature of the biotechnology knowledge may create conditions for greater pervasiveness, the effective exploitation of the opportunities thus generated is a strategic option and the ability to pursue with it depends on a number of other factors (market and management related) factors⁸.

⁸ Despite the potential range of opportunities, small firms may still chose to specialize, given resource or skills constraints. Technology entry barriers (Marsili, 2002) can also limit the choices open to new entrants, namely forcing them to specialize and/or enter in alliances with established firms, as is frequently the case in biotechnology (Orsenigo et al, 2001). On the other hand, since generic technologies are more distant from applications, firms exploiting them tend to take longer time searching for/developing specific applications (Costa et al, 2004).

3.2.2 Appropriability

Appropriability can be defined as the conditions concerning the protection of intellectual property assets against imitation, either through legal mechanisms (e.g., patents, copyright, formal non-disclosure agreements) or “natural” barriers to imitation, afforded by characteristics of the technology (tacitness, difficulty in reverse engineering) (Pisano and Teece, 2007). In general, higher appropriability conditions increase the likelihood that companies earn profits from their innovation. But, appropriability levels differ between sectors and the appropriability mechanisms that are available and effective also vary (Hurmelina-Laukkanen and Puumalainen, 2007). In the particular case of patents, the literature has shown that their incidence and effectiveness is confined to a few sectors, with alternative protection methods being extensively used in the majority of industries (Cohen et al. 2000; Arundel, 2001).

The different incidence of patents has been explained by Levin et al (1987) as related to the differences between technologies underlying these industries which influence patent effectiveness. They differentiate between “complex” technologies in which new products result from a combination of many elements (which may be separately patentable) and “discrete” technologies, in which innovations result from relatively stand-alone, isolated discoveries. Biotechnology is based on discrete technologies, so patenting of one specific invention can effectively be used to stop competitors from using it and thus may be critical to enable firms to benefit from their innovation. On the contrary, computing is based on complex technologies, where a product may require the combination of different components, which may be developed by different firms. Thus firms are less likely to have proprietary control over all the complementary components required to obtain a complete product, which leads to greater mutual dependence and to the development of extensive technology supply relationships. The latter may assume the form of cross-licensing when technologies are patented. But, in these contexts a loose appropriability regime can be a condition for innovation to occur, since it stimulates the development of new innovative combinations (Coriat et al, 2003). However, it has been shown that the recent increase in the levels of patenting had particular incidence in “complex product industries” where patents were traditionally less used (Hall, 2005).

In biotechnology, patents can also play other roles, besides being a protection mechanism. In fact they can be used by firms that have not yet developed a product to prove the presence of “knowledge assets”, thus being a basis for valuing the company, or a way to signal technological competence in the establishment of technological partnerships (Coriat et al, 2003; Rothaermel, 2002).

In some knowledge-intensive fields (of which biotechnology is an example) new firms are often exploiting knowledge that was directly transferred from academic research. This type of knowledge has some specific characteristics in what concerns appropriability. First of all, there is a greater possibility that its technology is patented and that the patent was transferred or licensed to the firm. In fact, not only scientific knowledge is, in principle, more abstract and codified (Arora and Gambardella, 1994) making patenting easier, but research organizations are putting growing emphasis on the IP protection of the technologies with commercialization potential. On the other knowledge associated with new scientific discoveries may have a high tacit component, which is derived from its very novelty and which endows it with “natural excludability” (Zucker et al, 1998). This can provide the firm with temporary protection against imitation, which is particularly important when formal mechanisms such as patenting are not viable or are less effective.

When protection through patents is not possible or has reduced effectiveness - and even when patent protection is possible the capacity to withstand patent litigation is limited as is often the case with small firms – technology-intensive companies will need to resort to other means to appropriate their innovations (Teece, 1986). One particularly effective mechanism is “lead-time”, that is the ability to be the first to enter a market and the capacity to stay ahead of competitors with a continuous stream of new technologies/products (Levin et al., 1987; Harabi, 1995; Cohen et al., 2000).

For instance in software the use of patent protection is not necessarily easy because of legal restrictions (Rao and Klein, 1994). While secrecy can have an important role, the high mobility of labour creates a constant risk (Atkins, 1998). Thus rapid development can be a better mode of protection (Hurmelinna-Laukkanen and Puumalainen, 2007). Indeed, “product proliferation” has been described as strategy often followed by software firms (Giarratana, 2004).

As was pointed out above, the capacity to generate new generations of technologies or products is often associated to the presence of more generic (general purpose) technologies, which can give rise to different market applications, providing firms with a “platform” that supports a continuous stream of development and thus enables them to sustain competitiveness through time. Presence of such a “technology platform” (which may or may not be protected by patents) can act as a strategic appropriability mechanism, providing firms with a lead time advantage upon competitors in the continued development of new generations of technologies or products. Hicks and Hedge (2005) found that small patent-based specialist suppliers that manage to survive and have long lasting success, develop technology that is more general purpose, has a broader range of applications (these technologies were also more basic and closer to science).

Kim and Kogut (1996) describe the advantages of a technology platform as the development of technological skills that give the firm the ability to diversify into related subfields following the branching of the underlying technological trajectory and the identified market opportunities. While this type of advantage is more likely to prevail in biotechnology, it will also be possible in software (Kim and Kogut, 1996).

In summary, an analysis of appropriability conditions at firm level will have to take into account both the possibility and effectiveness of patenting and the relative relevance of patenting and of other protection mechanisms. Considering that in technology-intensive fields lead time can be a particularly effective strategy, the extent to which this mechanism is used should also be of interest. Therefore, when addressing appropriability conditions we will consider both the presence of patents and the evidence of a lead-time strategy.

According to the literature reviewed above, appropriability through patents is more likely to be present in the biotechnology sector, although it may also be used by some more “science-based” software firms. On the other hand, appropriability through a lead time strategy is more likely to be the sole mechanism available to a substantial proportion of software firms as well as by biotechnology firms that do not patent (because of the nature of their knowledge, or for strategic reasons). However, it should be noticed that a lead time strategy can equally be adopted by firms who benefit from “natural” excludability (given the temporary nature of this protection) and by firm that patent, although in this case this strategy is more likely to be associated with the development of a platform technology (which is patented) that serve as basis to a sequence of licensable technologies and/or its combination with the development of own products.

It is to be expected that reliance on appropriability through patents will be a differentiating feature of a more science-based type of regime, which may or may not be combined with appropriability through lead time (some firms in these conditions are still at a too early stage to be possible to uncover its future options). On the other hand, sole reliance on appropriability through lead time is more likely to be a differentiating feature of an alternative regime.

The potential advantages of this approach to the identification of firms technological regime and therefore its potentially greater explanatory power concerning the impact of the nature of knowledge on the firms networking behaviour, will be subsequently tested empirically in the case of biotechnology and software firms.

3.3 An analytical model: some contributions

In this section, we will combine lessons from the previous sections to elaborate a set of propositions on the relations between the technological regime and its properties and the configuration of the related knowledge networks. This set of propositions consists of the pillars of the analytical model guiding the empirical work.

1. Due to the nature of knowledge to be accessed, mostly cutting edge complex scientific knowledge, science based firms (with an analytical knowledge base) prefer to resort to universities and research organizations. Thus, their knowledge networks have a much higher proportion of these organizations than more application oriented firms (the network composition is different).
2. The predominance of complex knowledge, collective knowledge creation and of exploration activities make long lasting collaboration and trust very relevant for science based firms. Therefore, their knowledge networks tend to have a higher proportion of strong ties. They favour the development of epistemic communities where exclusive and tacit knowledge can be shared. In addition, they are more able to prevent leakages of knowledge that has not yet reached the stage of applying for legal protection.
3. The relevance of radical innovation calls for the connection with a large and diversified set of partners in the case of science based firms. This diversification usually implies a multiplication of connections and an extension of the knowledge networks of these firms.
4. The presence of a clear division of labour between the different actors in the process of knowledge production and innovation may influence the network structure. In biotechnology, science based firms are in an intermediate position between scientific creation (universities) and its commercial application (established companies). This is likely to originate knowledge networks where science based firms act as brokers.
5. The importance attributed to knowledge networks becomes greater the more firms depend on crucial knowledge from external sources. This is the case of science based firms.

Empirical work will be presented in the next sections, drawing on this general framework.

4. METHODOLOGY

4.1 Empirical setting

The analysis was carried out using a sample of 46 Portuguese companies created between 1998 and 2008: 23 software and 23 biotechnology companies. In the case of *software*, we have focused on a particular application segment: *software for telecommunications*; in *biotechnology*, we focused on firms sharing the same knowledge base: *the molecular biology*. Our biotechnology firms can be regarded as the most science based group of firms within the sector, while in software our group corresponds to one of the most technologically advanced areas⁹. Tables 1 and 2 summarize the most relevant characteristics of the firms.

In the **software sector**, the sample is mostly composed of small to medium sized firms – 68% have less than 50 employees and the average number of workers is 117. Most companies (78%) were created between 1998 and 2003 and are located in the main metropolitan areas. Around 42% had a turnover (in 2007) between € 1 million and € 5 million. The average turnover was € 13.5 million.

Almost all companies (91%) carry out R&D activities. The average investment in these activities is 18% of the turnover and around a quarter of the total employees work on R&D activities. Only 5 companies applied patents. Also only 5 employ PhDs. In terms of sources of funding, a great majority relies on equity financing (90%). Eight resorted to some kind of public incentive, which represented, on average, only 4% of total funding.

As for the entrepreneurs, 37% of them hold a MBA and 10% hold a post-graduation in engineering, but only one holds a PhD. About 65% had worked or studied abroad over a significant period of time. Half of the entrepreneurs have conducted research activities at some point of their career.

In the **biotechnology sector**, the subset selected – molecular biology – belongs to the younger generation of Portuguese biotechnology: 78% have been created since 2004. Thus, several of them are still in an embryonic stage and only a few have fully developed their technologies/products. Twenty are research spin-offs.

⁹ The samples are very representative of the total population. In fact, we have identified 25 molecular biology companies and around 50 companies that produce software for telecommunications in Portugal.

Not surprisingly, most of these companies are very small: 70% have less than 10 employees, and the average number of employees is only 8. In 2007, 57% of the companies had a turnover of less than 100 000€. The firms are clustered around three main metropolitan areas.

The biotechnology companies exhibit a very high R&D intensity. The vast majority carries out R&D activities (78%). Their average investment in these activities is 107% of the turnover, since in a few cases R&D outlays exceed turnover. In terms of human resources, around 44% of the employees, on average, work in R&D activities. About half of the firms (48%) have patents. 15 companies out of 23 have at least one PhD. Doctorates represent, on average, one third of the workers. This high technological intensity can be partly explained by the fact that many companies are still developing their technologies. In fact, 30% have not yet introduced any technology or product into the market.

With regard to the sources of funding, the majority relies on equity (91%). Around one third resorted to venture capital. Half of the companies have received public incentives, which, on average, accounted for 20% of the total funding.

As to the entrepreneurs, their vast majority (65%) holds a PhD and nearly 86% have participated in research activities, studied or worked abroad for a significant period.

Table 1 - The companies

	Software	Biotechnology
	Number and valid percentage of companies	
Period of creation		
[1998 – 2003]	18 (78.3)	5 (21.7)
[2004 – 2008]	5 (21.7)	18 (78.3)
Total	23 (100.0)	23 (100.0)
Number of employees		
<10	8 (36.4)	16 (69.5)
10 - 49	7 (31.8)	7 (30.4)
50 - 499	6 (27.3)	0 (0.0)
>=500	1 (4.5)	0 (0.0)
Total	22 (100.0)	23 (100.0)
Average no. of employees	117	8
Turnover 2007 (€)		
0	0 (0.0)	6 (26.1)
]0 - 100.000]	2 (10.5)	7 (30.4)
]100 000 – 1 000 000]	4 (21.1)	5 (21.7)
]1.000.000 - 5.000.000]	8 (42.1)	5 (21.7)
]5.000.000 - 25.000.000]	2 (10.5)	0 (0.0)

]25.000.000 - 50.000.000]	1 (5.3)	0 (0.0)
>= 50.000.000	2 (10.5)	0 (0.0)
Total	19 (100.0)	23 (100.0)
Average turnover (2007)	13.5 million Euros	742 thousand Euros
Companies with R&D activities	21 (91.3)	18 (78.3)
Average % of R&D investment in the total turnover	14.8%	106.9%
Average % of employees in R&D activities	24.3%	43.5%
Companies with applied patents	5 (21.7)	11 (47.8)
Companies with PhDs	5 (21.7)	15 (65.2)
Average % of PhDs in total employees	2.5	32.6
Sources of funding		
Equity	19 (90.5)	20 (90.9)
Venture Capital	5 (23.8)	7 (31.8)
Public Incentives	8 (38.1)	11 (50.0)
Average % of equity in total funding	67.2	43.7
Average % of public incentives in total funding	3.8	19.5

4. 2 Data collection

Data about the 46 firms (in both sectors) was purposefully collected. Data on networks was obtained using a novel combination of complementary methods, involving both documentary information and in-depth face-to-face interviews with the founders (Sousa et al, 2011). The interviews, conducted in 2008, addressed both the entrepreneur and the firm and had an average length of 1.5 hours. They were based on two semi-structured questionnaires. The first focused on the entrepreneurs' personal (informal) network and its importance to the innovation process, allowing the collection of fine grained information about the people mobilized to access S&T knowledge, including the origin of the relationships and the type, nature and relevance of their contributions. The second addressed the firm's activities and strategy, with particular emphasis on knowledge production activities, organization and business strategies and formal cooperation arrangements.

More specifically these in-depth interviews included questions about R&D effort (in terms of expenditures and human resources), the nature of R&D activities conducted, the origin of the technology exploited at start-up and the mechanisms of appropriability used by the firm. They also included a set of questions about the relations mobilized to access S&T knowledge that enable us to characterize the type of relation (formal or informal), the frequency of interaction

(in the case of informal relations), the number of collaborations (in the case of formal relations) and the type of partner.

During the interviews, the entrepreneurs were also asked to rate, on a scale from 1 to 7, the *importance attributed* to formal relationships with other firms and with universities and other research organizations (both denoted as “universities”) and to informal relationships (not distinguishing the type of actor) to access both scientific and technological knowledge.

4.3 Network reconstruction and analysis

Using the data obtained from the interviews and the documentary information, we were able to (re)construct the individual firms’ knowledge networks (ego-networks). These networks encompass the relationships that were mobilized to access scientific and technological knowledge. In these networks, we have distinguished between formal and informal relations. Formal relations include the participation of the firm in collaborative projects, technological partnerships and patents with other organizations. Informal relations include the ties with individuals to whom the entrepreneurs resort to get information about innovative opportunities and access to scientific and technological knowledge. Those individuals were assigned, for operational purposes, to their affiliation organization(s). Total networks, at firm level, are obtained through the aggregation of formal and informal networks.

The level of intensity of the ties has been depicted in the literature as a function of two factors: the amount of resources exchanged and the frequency of contact between two organizations (Zhao and Aram, 1995). In this paper, the intensity of the ties – i.e. whether the tie is strong or weak - was obtained using two indicators:

- The frequency of contacts: in the case of the informal networks, a tie is strong when the contact takes place at least once a month; in the case of formal networks a tie is strong when there is more than one collaboration with the same organization.
- The existence of more than one type of tie with the same organization: a tie between two entities is strong whenever different types of relations (formal and informal) are established between them.

Thereafter, a detailed analysis of the composition and structure of the networks was conducted, using Social Network Analysis (Wasserman and Faust, 1994) and supported by the UCINET software.

Network composition deals with the diversity of actors. In this research the following types of actors are considered: firms from the same sector, firms from other sectors, universities and research centres, science & technology parks, financial institutions, and other institutions such as professional and trade associations. Their importance is assessed through the respective proportion in the total number of actors.

The *network structure* can be characterized in terms of density. The traditional density measure – the ratio between the number of ties that are present in the network and the theoretical maximum - is not applicable in our case, since the reconstructed networks only encompass the firms' ego-networks (thus excluding indirect ties). Networks with a bigger proportion of strong ties are denser. So, to characterize network density we have used the proportion of strong ties in the total number of ties.

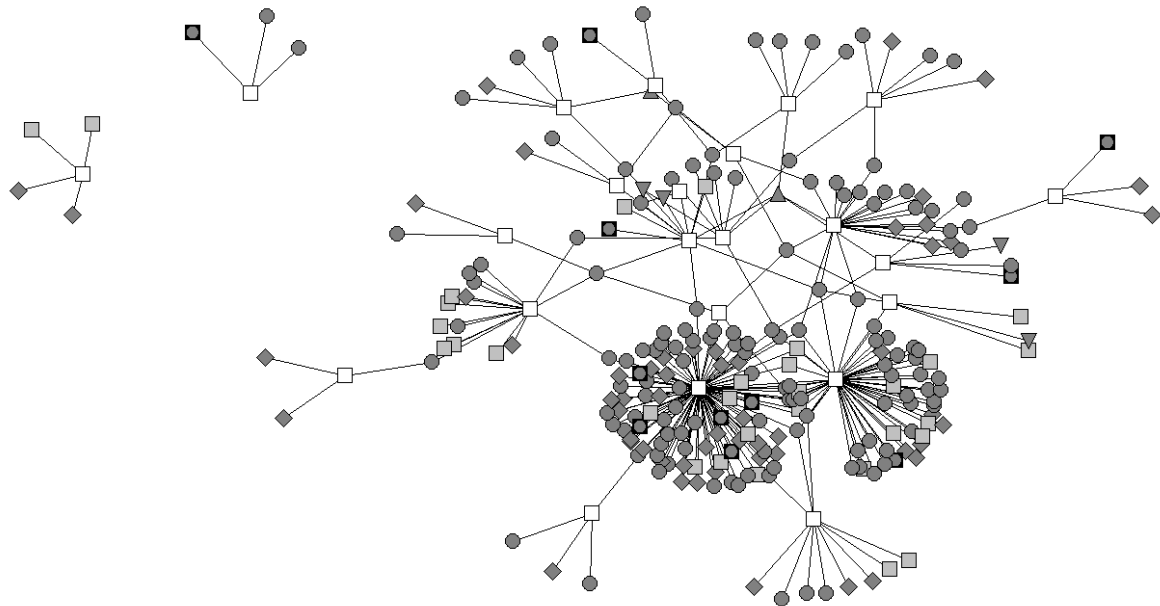
To capture the *positioning of each firm* in the respective overall knowledge network we have considered two centrality measures from the social network analysis literature: the degree centrality and the betweenness centrality.

Degree centrality is the number of connections an actor has (Freeman, 1978/79), i.e., the number of direct ties one firm has to other organizations in the network. As a result, the most central company is the one with the largest number of ties (links/connections) with other organizations, having access to more of the whole network's resources (in this case S&T knowledge).

The *betweenness centrality* considers the number of times an actor lies between each pair of other actors, indicating whether an organization plays the role of a broker who can exert control over others. Brokers have important, non-redundant knowledge to provide to other actors who would otherwise be isolated from the network.

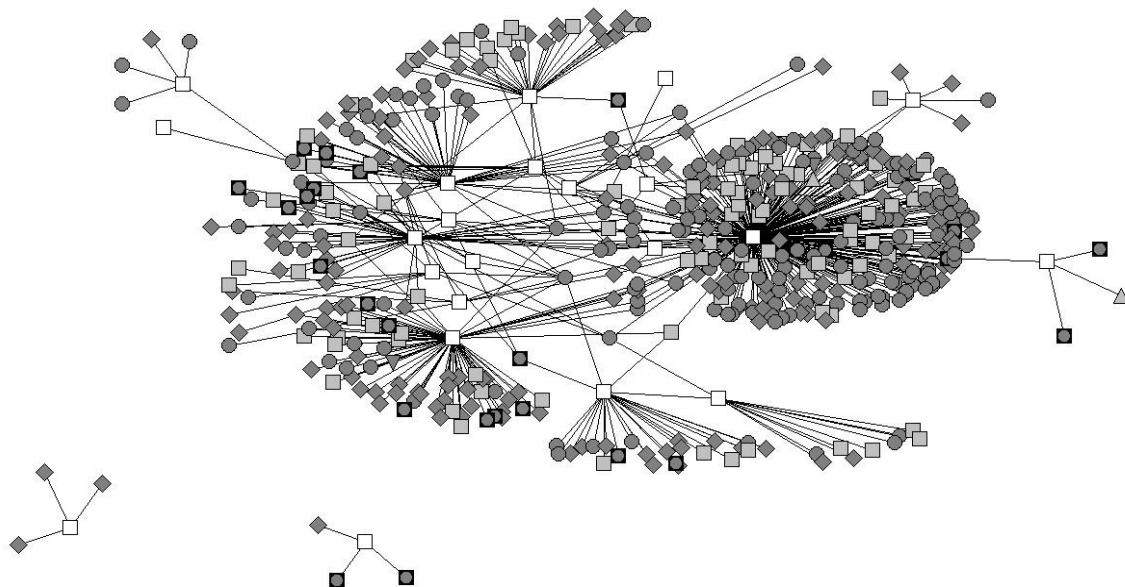
As proposed by Freeman (1978/79), since we are considering sectoral networks with different sizes and densities (Hanneman and Riddle, 2005), we use relative (normalized) measures of centrality, that is the absolute measures divided by the maximum possible value in each network and expressed as a percentage. These centrality measures were calculated on the basis of the respective sectoral network, that is, the sectoral network where each firm is embedded. These sectoral networks, represented in Figures 1 and 2, are obtained through the aggregation of firm-based ego-networks, considering all the interviewed firms in each sector.

Figure 1 – Knowledge network of biotechnology firms



Legend: interviewed firms (white squares), firms from the same sector (grey squares), firms from other sectors (diamonds), universities and research organizations (circles), financial institutions (upward triangles); science and technology parks (downward triangles) and other organizations (circles-in-box)

Figure 2 – Knowledge network of software firms



Legend: interviewed firms (white squares), firms from the same sector (grey squares), firms from other sectors (diamonds), universities and research organizations (circles), financial institutions (upward triangles); science and technology parks (downward triangles) and other organizations (circles-in-box).

The *importance attributed to formal relationships* to access S&T knowledge was obtained through the sum of the ratings attributed to relations with other firms and to relations with universities and other research organizations to access scientific knowledge and to access technological knowledge. A similar procedure was followed regarding informal relationships, in order to obtain the *perceived importance of informal networks* to access knowledge relevant for innovation. Finally, *the perceived importance of knowledge networks* is obtained through the aggregation of the ratings attributed to formal and to informal relations.

5. A MICRO-LEVEL APPROACH TO BUILDING TECHNOLOGICAL REGIMES

5.1 Operationalization of regime properties

The building of firm-based technological regimes required the operationalization of the regime properties identified and discussed in the section 2, namely regarding to technological opportunity and appropriability. Table 2 summarizes the binary variables that were used to capture the key dimensions of those properties.

Table 2 - Description of the variables related to technological regimes properties

Property	Dimension	Variable	Values
Technological opportunity	R&D effort	R&D employees in total employment	1 when the firm has an R&D effort above 50%; 0 otherwise ^a
	Contents of R&D activities	Performance of applied research and development	1 if the firm performs applied research and development; 0 otherwise.
	Sources of opportunity	Origin of the technology	1 if the technology was transferred from a research organization; 0 otherwise
Appropriability	Appropriability through patents	Applied patents	1 if the firm has applied for a patent; 0 otherwise.
	Appropriability through lead time	Strategic orientation towards product diversification	1 if the firm has adopted a product diversification strategy; 0 otherwise.

^a The choice of this cut-off point at 50% was based on a cluster exercise, performed with a continuous variable and the two step cluster procedure. In this previous exercise, we found that this threshold level clearly separates two groups of firms.

Regarding the *R&D effort*, the choice of an indicator based on human resources is explained by the nature of the firms: not only several preferred not to disclose their sales and/or R&D expenditures, but also a few (biotechnology) still did not have sales or had negligible sales only, despite a strong investment in R&D.

The *content of R&D activities* is seized by the type of activities conducted by the firm: basic research, applied research and development. During the interviews we found that biotechnology and software firms attributed substantially different meanings to the concept of “basic research”. For that reason, we discarded the former and built a variable that combines applied research and development.

When measuring the *sources of opportunity* we focused on the *relative importance of scientific advances*, indicated by the academic origin of the technology that led to the creation of the firm. Thus, our variable reflects the formal or informal transfer of the original technology from a research centre to the company.

As pointed out above, the combination of relevance of scientific knowledge (more generic knowledge) with evidence of extensive product (or technology) diversification can be regarded as a proxy to *pervasiveness*. Thus pervasiveness can be measured combining the indicators of importance of academic science (origin of the technology) and of lead time strategy (product diversification or presence of a technology platform) which is described below.

Appropriability through patents relates to the presence of patents (international or national). Due to the youth of firms, namely in biotech, and to the length of time that elapses between the submission and assignment of a patent we have not considered patents already granted but patent applications (European and US). We also included both national and PCT applications. Despite the limitations of both, taken together they reveal a steady intention to patent.

The *appropriability through lead time* was operationalized considering the adoption of an extensive product diversification strategy. This strategy implies that companies develop subsequent waves of products that allow them to stay one step ahead of competitors and (at least) maintain their market share.

5.2 Identifying firm-based technological regimes – a cluster analysis

In order to investigate whether there is intra-sectoral variety and/or inter-sectoral regularities in terms of technological regimes, in our two sectors, we have conducted a cluster analysis. We have considered the same set of binary variables presented in the previous section and used the hierarchical cluster procedure with furthest neighbour linkage cluster method and binary squared Euclidean distance measure.

As a first step we have performed two cluster exercises, one for biotechnology and one for software. The objective was to investigate if it was possible to group firms in homogeneous

categories using the variables that were defined in the previous section, i.e. whether regime and sector effectively overlapped in biotechnology and in software.

Having concluded for the presence of heterogeneity within each sector, we have investigated whether firms would rather be grouped according to technological regimes that do not correspond exactly to sector boundaries. For this purpose, we have performed a new cluster exercise including all firms from both sectors, in order to investigate whether there were regime-related regularities across sector boundaries.

We have found two different clusters¹⁰ that do not correspond to the boundaries of the sectors, which can be an indicator of the existence of “firm-based technological regimes”.

The first cluster includes seven biotechnology firms, mostly belonging to the group engaged in the long term development of platform technologies. It also includes nine software firms that stand out as more research oriented and engaged in more advanced technologies. Globally, a qualitative evaluation of this group of firms, based upon a wide range of information, obtained from the interviews, suggests that it corresponds to a more science-based pattern of behaviour. This group is called the “science-based technological regime” (SB-TR).

The second cluster includes 14 software firms that fit the typical behaviour of the sector, and 16 biotechnology firms, mostly corresponding to the group that is applying the technology to customer oriented applications, such as diagnostic tools or specialised services. This group is called the “application oriented technological regime” (AO-TR).

Table 3 summarizes the characteristics of these two firm-based regimes along the selected technological regimes variables. It also presents the values for the variables for the two sector-based regimes. We can observe that TR-SB, as compared with TR-AO, has a higher proportion of firms with appropriation through patents and through lead-time, and combining applied research and development. However, it also has a higher proportion of firms with more than 50% of their workforce engaged in R&D and a lower proportion of firms using technology that had its origin in the university than TR-AO¹¹. Regarding the sector based regimes, biotech

¹⁰ The number of clusters was defined using the Calinski-Harabasz pseudo F index and the Duda-Hart stopping-rule index.

¹¹ A closer analysis of the interviews suggests that the firms in the SB-TR have more R&D employees in absolute terms and thus a higher absolute R&D effort, but because they are generally bigger in terms of number of employees, this fact is not captured when we consider proportions. Similarly, interviews suggest that these firms tend to be highly knowledge-intensive firms that are developing in-house science-based products/technologies, often in close cooperation with universities. Thus they tend to consider that the bulk of their technology was developed internally and not transferred from the parent organization.

firms, compared with the software, exhibit higher values for all variables except for the appropriation through lead-time.

Table 3 - Technological Regimes characteristics along selected variables – Proportion of firms in each regime

Variable	Firm-based TR		Sector-based TR	
	SB-TR	AO-TR	Biotech	Software
R&D workers > 50%	0.25	0.33	0.48	0.13
Applied research and development	0.44	0	0.22	0.07
Technology transferred from a research organization	0.25	0.43	0.48	0.26
Patent application	0.69	0.17	0.43	0.26
Appropriability through lead time	1	0.37	0.52	0.65

The results reveal the existence of a group of software firms and of a group of biotechnology firms whose behaviour appears to be closer to firms in the other sector rather than to those in their own, thus departing considerably from the behaviour typically ascribed to the respective sector. This is an interesting finding that confirms the presence of intra-sector heterogeneity and of inter-sector regularities, in terms of technological regimes.

These results suggest that the use of standard indicators (namely from public available data bases) can elude sectoral differences in the meaning of the variables. One of the merits of our methodology is that it enables us to achieve a greater adherence to firm behaviour at the micro level, since we have gathered abundant qualitative data.

5.3 Network configurations

Since we are interested in understanding whether there are differences between firms in different regimes with respect to the configuration and importance of the relationships established to access scientific and technological knowledge, we have used the network measures described above to characterize the technological regimes in terms of knowledge networks. In table 4 we can observe the characterization of the technological regimes, both firm and sector based, in terms of the firms' network configuration and importance attributed to knowledge networks.

Firms in the SB-TR, as compared with firms in the AO-TR, attribute greater importance to their knowledge networks, which are larger, have a lower proportion of universities and strong ties and a higher proportion of firms. Regarding sector-based regimes, biotechnology firms, compared with the software ones, exhibit a higher value for the proportion of universities and for all variables related to structure and a lower value for the proportion of firms and the variable of perceived importance.

**Table 4 – Technological regimes and network configuration and perceived importance –
Average values in each regime**

Variable	Firm-based TR		Sector-based TR	
	SB-TR	AO-TR	Biotech	Software
% of universities	0.46	0.50	0.66	0.31
% of firms	0.44	0.36	0.23	0.55
% of strong ties	0.31	0.45	0.53	0.28
Degree centrality	9	2	5	4
Betweenness centrality	11	12	9	6
Perceived importance of firm knowledge network ^a	53	39	40	46

^a Perceived importance variables are ordinal. For them we report median values.

The question now is whether “firm-based technological regimes”, as an alternative to sectors, have some explanatory power regarding variety in firms’ networking behaviour.

6. INFLUENCE OF TECHNOLOGICAL REGIMES ON KNOWLEDGE NETWORKS

6.1 Definition of the models

In this section, we investigate the influence of technological regimes on the configuration and perceived importance of the innovation networks built by biotechnology and software firms. For this purpose, we compare the explanatory power of the two notions of technological regime, as previously discussed: a) the regime associated to the sector where firms operate; b) the regime defined independently of the sector, i.e. the “firm-based technological regimes” constructed earlier.

We have run four sets of regressions to explain respectively: 1) the perceived importance of the knowledge networks; 2) the composition of the knowledge networks; 3) the structure of the knowledge networks; 4) the positioning of firms in the respective knowledge network. In order to address the two different approaches to the technological regime we have performed the various sets of regressions for two different independent variables, which express the two different approaches to the technological regime: i) a dummy for the sector-based technological regime (biotechnology vs. software): ii) a dummy for the “firm-based technological regimes” (Table 5).

Table 5 - Independent variables description

Variable	Description	Type	Values
Sector-based TR	Sectoral affiliation	Dummy	1 if biotech; 0 if software
Firm-based TR	Firm-based technological regime affiliation	Dummy	1 if TR-SB; 0 if TR-AO

Dependent variables are presented in Table 6. **The first group of regressions** attempts to capture the effect of the technological regime (sector-based vs. firm-based) on the *perceived importance of knowledge networks*. In these regressions, the dependent variable reflects the importance of knowledge networks *as perceived by the entrepreneurs and it unfolds in fact into three variables* which represent the importance attributed by each firm: i) to formal networks; ii) to informal networks; iii) to networks taken globally (both formal and informal). Since these are non-negative count variables, count models are preferred to linear regression models (OLS). The Poisson regression approach is appropriate for such data (Greene, 2011). However, its application requires the equity between the conditional mean and variance, which does not occur in our data. In these circumstances it is recommended to use the negative binomial estimation, which is an extension of the Poisson model.

The second group of regressions captures the effect of the technological regime (sector-based vs. firm-based) on the *network composition*. We have considered two different dependent variables concerning the knowledge network of each firm: i) the share of universities within the total number of actors; ii) the share of firms within the total number of actors. Since these variables are proportions the OLS estimation is not recommended. We have chosen to treat the proportion as a censored continuous variable and used two-limit Tobit regressions (Long, 1997).

In the third set of regressions, we investigate the influence of the technological regime (sector-based vs. firm-based) on the *network structure* and estimate its effect on the proportion of strong ties in each firm's knowledge network. For this variable we have used two-limit Tobit models.

Finally, **the fourth set of regressions** assesses the effect of the technological regime (sector-based vs. firm-based) on the *positioning of each firm* in the respective sectoral knowledge network. We have considered the two previously mentioned centrality measures: degree and betweenness. Once again we are dealing with proportions and thus the two-limit Tobit was used.

Table 6 - Dependent variable description

Variable	Description	Mean ^a	SD	Min	Max
Perc Import	Perceived importance of firm knowledge network	43		7	80
Perc Import Formal	Perceived importance of firm formal knowledge network	26		4	52
Perc Import Informal	Perceived importance of firm informal knowledge network	19		4	28
Univ	Proportion of universities in firm knowledge network	0.47	0.37	0	1
Firm	Proportion of firms in firm knowledge network	0.39	0.33	0	1
Strong ties	Proportion of strong ties in firm knowledge network	0.42	0.34	0	1
Degree	Normalized degree centrality of the firm in the knowledge network	4.63	9.19	0	47.99
Betweenness	Normalized betweenness centrality of the firm in the knowledge network	4.17	14.86	0	77.43

We have considered the same set of control variables in all regressions (Table 7). The first is the age of the firm (in years). The second is the firm size, measured by the number of employees in 2007. The third refers to the presence of venture capital, which is likely to capture the firm's growth potential. Venture capital companies tend to invest in firms with a high potential of growth, even if it is still latent. Often, a qualitative appreciation is made of (or even a bet on) the potential of the "knowledge assets" of the firm, or of the quality of the related human resources. Therefore, venture capital investment can be regarded as having a signalling and/or brokering effect on the establishment of relationships between the innovative company and its technology partners (Stuart et al., 1999). Finally, we control for the "business model" – which is an important source of variation in firms' behaviour (Chesbrough and Rosenbloom, 2002). We have considered two different business models defined by the strategic intention to commercialize (i) products or (ii) technology (Gans and Stern, 2003). The variable used is the importance attributed by the firm to the creation/development of a marketing department, which signals the first strategy.

Table 7 - Control variables description

Variable	Description	Type	Values
Age	Firm age (years)	Continuous	Mean = 6 SD = 3
Size	Number of employees in 2007	Continuous	Mean = 39 SD = 86
Venture capital	Presence of venture capital	Dummy	1 if there is venture capital; 0 otherwise
Business model	Importance attributed to the creation/development of marketing department	Dummy	1 if it is a priority ; 0 otherwise

6.2 Econometric results

In table 8, results of the first two regressions show that firm-based regimes have a significant impact on the perceived importance of knowledge networks, contrarily to sector-based ones. The positive sign of the coefficient means that firms in the science-based technological regime (SB-TR) attribute more importance to networks than firms in the application-oriented technological regime (AO-TR). This result holds for all networks considered (total, formal and informal).

Results also indicate a positive and significant relation between age and the perceived importance of knowledge networks, which holds for all types of networks. So, our data suggest that older firms perceive knowledge networks as more important than younger ones.

Table 8 - Estimation of the sector/technological regime effect on the perceived importance of knowledge networks (Negative Binomial Regression)

	Total		Formal		Informal	
	(1)	(2)	(3)	(4)	(5)	(6)
Sector-based TR	0.104 (0.145)		0.133 (0.241)		0.041 (0.111)	
Firm-based TR		0.322*** (0.124)		0.448** (0.215)		0.157* (0.094)
Age	0.091*** (0.025)	0.076*** (0.022)	0.099** (0.042)	0.084** (0.037)	0.074*** (0.019)	0.065*** (0.017)
Size	-0.0003 (0.001)	-0.001 (0.001)	-0.0003 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.0003 (0.001)
Venture Capital	0.182 (0.146)	0.126 (0.139)	0.203 (0.248)	0.120 (0.238)	0.142 (0.109)	0.112 (0.107)
Business model	-0.041 (0.127)	-0.024 (0.118)	-0.033 (0.218)	-0.021 (0.204)	-0.039 (0.095)	-0.023 (0.091)
C	3.148*** (0.210)	3.182*** (0.148)	2.517*** (0.343)	2.534*** (0.254)	2.443*** (0.167)	2.460*** (0.118)
No. observations	46	46	46	46	46	46
Log likelihood	-194.953	-192.007	-188.356	-186.387	-145.330	-144.064
LR χ^2	13.13**	19.02**	5.86	9.80*	16.25***	18.78***
Alpha	0.149	0.126	0.461	0.409	0.038	0.032
Likelihood-ratio test of alpha = 0	143.57***	113.47***	199.17***	166.06***	6.09***	4.32**

Notes: robust standard errors are given in the parentheses *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level

Results for the second set of regressions, that test the impact of technological regimes on *network composition*, are reported in Table 9. There we find evidence of an influence of the sector-based, but not of the firm-based regime, on the proportions of universities and of firms in knowledge networks. The signs of the coefficients reveal that biotechnology firms' knowledge networks have a higher proportion of universities and a smaller proportion of companies when compared with those of software.

We also see a positive relation between the proportion of firms in the knowledge networks and the presence of venture capital. This suggests that the signalling effect of venture capital is particularly important when firms establish relations with other firms.

Table 9 - Estimation of the sector/technological regime effect on the network composition (Tobit regressions)

	Universities		Firms	
	(1)	(2)	(3)	(4)
Sector-based TR	0.365*** (0.099)		-0.344*** (0.097)	
Firm-based TR		0.003 (0.103)		0.005 (0.099)
Age	0.013 (0.017)	-0.013 (0.017)	0.003 (0.016)	0.027 (0.017)
Size	-0.0004 (0.001)	-0.001 (0.001)	0.0001 (0.001)	0.0004 (0.001)
Venture Capital	-0.149 (0.098)	-0.184 (0.112)	0.178* (0.096)	0.210* (0.109)
Business model	-0.059 (0.085)	-0.121 (0.096)	-0.114 (0.083)	-0.055 (0.092)
C	0.309** (0.146)	0.689*** (0.119)	0.541*** (0.142)	0.183 (0.115)
No observations	46	46	46	46
Log likelihood	-6.302	-12.262	-5.037	-10.646
LR χ^2	18.42**	6.50	18.27***	7.05
Σ	0.277	0.316	0.270	0.305

Notes: robust standard errors are given in the parentheses *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level

Table 10 reports the results of the third set of regressions that test the impact of technological regimes on the network structure. We found evidence of the relevance of the sector-based technological regime on the proportion of strong ties. Biotech firms tend to have networks with a higher share of strong relations. Age also emerges as significant and the negative coefficient for this variable reveals that older firms have looser knowledge networks with a smaller

proportion of strong ties. This is consistent with the predictions of the network literature, namely that, as firms evolve, the structure of their networks change. In early stages, ties are mainly informal and based on previous personal contacts and the network structure conducive to success is more cohesive. Later on, relations tend to be more formal and centred on firm's business activity, and structural holes become more critical for success (Hite and Hesterly, 2001).

Table 10 - Estimation of the sector/technological regime effect on the proportion of strong ties

	(Tobit regressions)	
	(1)	(2)
Sector-based TR	0.203* (0.104)	
Firm-based TR		-0.084 (0.097)
Age	-0.044** (0.017)	-0.056*** (0.017)
Size	0.001* (0.001)	0.001 (0.001)
Venture Capital	-0.068 (0.103)	-0.073 (0.107)
Business model	0.100 (0.089)	0.055 (0.091)
C	0.481*** (0.153)	0.704*** (0.113)
No. observations	46	46
Log likelihood	-8.550	-9.999
LR χ^2	15.06***	12.16**
Σ	0.291	0.301

Notes: robust standard errors are given in the parentheses *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level

The results of the model estimation for degree centrality (Table 11) reveal that both the sector-based and the firm based technological regime influence the positioning of firms in the respective knowledge network. The positive signs of the coefficients indicate that biotechnology firms and firms belonging to the SB-TR have larger knowledge networks in relative terms. Age and size of the firms also have a positive effect on their degree: older and larger firms tend to establish more relations to access S&T knowledge.

Considering betweenness centrality, we have found evidence of the relevance of sector-based technological regime: biotechnology firms tend to have higher betweenness centrality and thus to perform a brokerage function. The firm's age and business model also have an impact: older

firms and firms focusing the commercialization of technologies (instead of products) tend to have a brokerage role in their knowledge networks.

Table 11 - Estimation of the sector/technological regime effect on the network positioning (Tobit regressions)

	Degree		Betweenness	
	(1)	(2)	(3)	(4)
Sector-based TR	6.580** (2.556)		8.219* (4.492)	
Firm-based TR		4.967** (2.373)		3.432 (4.194)
Age	0.826* (0.428)	0.197 (0.403)	2.457*** (0.752)	1.762** (0.713)
Size	0.057*** (0.014)	0.047*** (0.014)	-0.021 (0.025)	-0.031 (0.025)
Venture Capital	0.189 (2.539)	-1.223 (2.611)	-2.364 (4.460)	-3.684 (4.614)
Business model	-0.667 (2.191)	-1.176 (2.213)	-7.485* (3.848)	-8.464** (3.912)
C	-5.271 (3.766)	0.792 (2.750)	-5.855 (6.615)	2.154 (4.861)
No observations	46	46	46	46
Log likelihood	-155.781	-156.780	-181.697	-182.980
LR χ^2	22.06***	20.06**	14.44**	11.87**
Σ	7.154	7.311	12.566	12.921

Notes: robust standard errors are given in the parentheses *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level

7. DISCUSSION

In this section, the empirical results are discussed in light of the theoretical framework and particularly of the propositions elaborated in section 3.3. In addition, we draw conclusions on the explanatory potential of firm-based versus sector-based technological regimes. These two regime approaches were used in the analysis, since we found a significant heterogeneity of firms' innovative behaviour within each sector, biotechnology and software. This led us to consider a firm-based approach and build two alternative firm-based regimes – science-based and application-oriented - that cut across sectoral boundaries.

The results show that, overall, the nature of knowledge, expressed through the technological regime, has some impact upon the importance attributed by firms to knowledge networks, as well upon the actor composition and the structure of these networks.

More specifically, they permit to gain a better understanding of some key elements of the relationship between networks and regime, which were advanced as theory-driven propositions.

The first proposition is related to the composition of the knowledge networks. As expected science-based firms have a higher proportion of universities, while more application oriented firms have a higher proportion of firms in their knowledge networks.

In this case the sector-based regime is more powerful to capture the differences in the knowledge bases. Biotechnology firms rely more extensively in university research than software firms. Biotechnology has originated from new scientific discoveries and its development continues to draw extensively on scientific research (Zucker et al, 2002). This is supported by previous studies that have shown that new biotechnology firms establish extensive relationships (formal and informal) with research organizations both to develop early technologies (when the parent research organization is often critical) and to maintain competitive edge over time (McMillan et al, 2000; Levitte and Bacgchi-Sen, 2010). As to software firms, although we cannot consider that relations with universities are unimportant to access knowledge, these relations are important overall to access talented highly skilled engineers in order to continually improve the skills base of the companies (Giarratana, 2004).

The results are also aligned with the literature on knowledge bases, confirming that relations with research organizations are more frequent in the case of firms where the analytical knowledge base dominates (biotechnology) and interactions with clients and suppliers for problem solving are more frequent for those where a synthetic knowledge base dominates (software) (Moodysson et al, 2008; Plum and Hassink, 2011).

The second proposition relates to the network structure expressed in terms of the proportion of strong ties. Results show that, as expected, science-based firms have a higher proportion of strong ties in their knowledge networks.

Again, the sector-based regime is more powerful to capture differences in the knowledge bases. Biotechnology firms rely more on strong relations to access the S&T knowledge. This result can be explained by the greater complexity of knowledge in biotechnology (Hansen, 1999). It may also be related with the fact that the production of scientific knowledge frequently takes place in the context of “epistemic communities” i.e., tightly knitted groups of scientists that share the same knowledge base as well as common codes of behaviour (Breschi and Lissoni, 2001). Biotechnology firms have interest in participating in those communities, which permit exchange of knowledge not intelligible for external actors. This is particularly relevant in the case of new

scientific discoveries, where knowledge is highly tacit and characterized by “natural exclusivity”, i.e. only those who were involved in the development, will have effective access to the knowledge and possess the know-how necessary to replicate it (Zucker et al, 1998). Finally, the predominance of strong relations may be also related to the fact that knowledge assets are particularly important for biotechnology firms (they are their main – sometimes unique - asset), and thus trust is critical when knowledge is developed in collaboration (Smith-Doerr and Powell, 2005).

The third proposition is focused on the size (degree) of the networks. As expected we found that science-based firms have larger knowledge networks. The result holds for both types of regime considered – sector-based and firm-based. It reveals the importance, for these firms, of being connected with a large set of organizations, namely because they need to establish relationships with a diverse set of organizations (Baum et al, 2000).

The fourth proposition is related with the brokerage role of firms in the networks. As expected science-based firms perform a more relevant brokerage function in the networks were they are embedded. Once again it is the sector-based regime that captures the differences in the knowledge bases. As previous mentioned, this may be explained by the fact that biotechnology firms frequently act as intermediaries between scientific production that takes place in research organizations and its commercial exploitation by large established companies (Stuart, Ozdemir and Ding, 2007). Additionally, as discussed earlier, biotech firms often belong to scientific communities and more central firms in these communities may have a brokerage role.

Finally, **the fifth proposition** deals with the perceived importance of knowledge networks. The results confirm the expectation that science-based firms perceive knowledge networks as more important than application-oriented firms. In this case it is the firm-based regime that captures the differences in the knowledge bases. The relevance attributed to the networks reflects the entrepreneurs’ perceptions. These are more likely to be influenced by the context where the firms effectively operate, which is not necessarily sector-determined.

Summing up, the results corroborate all the propositions raised and also the greater explanatory capacity of sector- based technological regimes versus firm-based regimes that cross sectoral boundaries.

8. CONCLUSIONS

The main goal of the paper was to identify and understand the influence of technological regimes under which firms operate on the composition and structure of their networks for accessing and exchanging knowledge. The empirical results show that such influence exists and contribute to explain how it takes place.

It was found that distinct technological regimes, based on the firms' sectoral classification - one more science-based (corresponding to biotechnology) and the other more application-oriented (corresponding to software) - are associated with firms' knowledge networks that display different properties. These results are in accordance with what was theoretically expected, as expressed by a set of propositions, whose development draw on the combination of two parallel but so far largely unconnected bodies of literature: on technological regimes and on knowledge networks. These propositions are intended to throw a bridge between the two research domains and guide empirical work.

More specifically, we found that knowledge networks of biotechnology firms are composed of a higher proportion of universities and research organizations, when compared with software where other firms predominate; and have relatively more strong ties and a greater number of connections to other partners, also when compared to software ones. In addition, biotechnology firms tend to act more frequently as brokers between research organizations and larger established companies that are often responsible for the downstream development and/or commercialization of their technologies/products.

In consonance with recent research (Leiponen and Dredjer, 2007; Peneder, 2010), it was found that if we depart from the assumption of the sectoral identity of regimes and attempt to identify regularities and differences in terms of their properties, two regimes emerge that cut across the sectors boundaries and encompass firms from both. This suggests that despite the sectors' structural elements, there remains some scope for variety.

Some authors have explained this heterogeneity with the potential for variety that derives from the different strategic responses by firms to similar conditions. Other authors have attributed it to the fact that sectors are defined according mostly to products and, therefore, a sector may encompass different technologies. Both explanations seem pertinent. However, the firm-based technological regimes, which were reconstructed in alternative to the sector-based ones above mentioned, had a lower explanatory power of variety in network configurations. Remarkably firm-based regimes emerged as superior in the case of firms' perception of the importance of

networks, which is more likely to be influenced by the actual technological environment faced by the individual firm.

In addition to theoretical and empirical results, the research also provided some methodological novelty, namely through: the combination of qualitative and quantitative information, which proved to be very useful for the definition of the variables and the interpretation of the results; the use of micro-data purposefully collected, together with information available from several data bases; and finally the application of a diversified set of techniques (cluster analysis, econometrics and social network analysis). The results seem to prove the adequacy of the methodological approach.

A remark must be made, concerning the empirical data: the quality and wealth of the data obtained for the networks is not always matched by the data on business organization and strategies, which sometimes are not completely satisfactory. This calls for future refinements at this level.

In spite of these limitations, our findings offer new insights into the relationship between firms' technological environment and one key element of firms' innovative behaviour: their knowledge networking strategies.

The results may also be relevant for policy makers and entrepreneurs on several grounds, since they point out that: 1) overall, knowledge networks appear as particularly important to the most advanced group of firms, those that need to access and exchange new scientific knowledge; 2) universities and research organizations play a crucial role by "nurturing", in a permanent way, the most advanced economic sectors, i.e. those that develop and apply cutting edge knowledge. The quality of universities' research is crucial to the development of knowledge-intensive sectors, not only through the training of highly skilled professionals, spin-offs creation and knowledge spill-overs, but also through the formal and informal relations they maintain with firms; 3) for science-based firms, a mixed knowledge network combining strong ties and brokerage may be an adequate strategy, since it favours, simultaneously, a high degree of trust and identity among partners that share and exchange complex, tacit and valuable knowledge (strong ties); and the permanent provision of new ideas and non redundant knowledge (brokerage); 4) the diversification and expansion of links with a variety of partners seems to be associated with radical innovation, while the predominance of routinized links is more likely to be associated with incremental innovation and product and process enhancement. These conclusions may contribute to support strategy definition and policy formulation. In addition, they raise some challenging questions for further research.

REFERENCES

AHUJA, G. (2000), “Collaboration networks, structural holes, and innovation: a longitudinal study”, *Administrative Science Quarterly*, pp. 45: 425-455.

ARCHIBUGI, D. (2001), “Pavitt’s taxonomy sixteen years on: A review article”, *Economics of Innovation and New Technology*, pp. 10(5), 415-425.

ARUNDEL, A. (2001), “The relative effectiveness of patents and secrecy for appropriation”, *Research Policy*, 30(4): 611-624.

ARUNDEL, A., VAN DE PAAL, G. and SOETE, L. (1995), “Innovation strategies of Europe’s largest industrial firms”, MERIT, Maastricht.

ATKINS, M.H. (1998), “The role of appropriability in sustaining competitive advantage – an electronic auction system case study”, *Journal of Strategic Information Systems*, 7, pp. 131–152.

AUTANT-BERNARD, C. (2001), “The geography of knowledge spillovers and technological proximity”, *Economics of Innovation and New Technology*, 10, pp. 237-254.

AUTIO, M. (1997), “New technology-based firms in innovation networks Symplectic and Generative”, *Research Policy*, 26, pp. 263-281.

BAUM, J.A.C., CALABRESE, T. and SILVERMAN, B.S. (2000), “Don't go it alone: alliance network composition and start-ups' performance in Canadian biotechnology”, *Strategic Management Journal*, 2, pp. 267-294.

BRESCHI, S. and LISSONI, F. (2001), “Knowledge spill-overs and local innovation systems: a critical survey”, *Industrial and Corporate Change*, 10, pp. 975-1005.

BRESCHI, S. and LISSONI, F. (2009), “Mobility of skilled workers and co-invention networks: an anatomy of localized knowledge flows”, *Journal of Economic Geography*, 9, pp. 439–468.

BRESCHI, S., MALERBA, F. and ORSENIGO, L. (2000), “Technological regimes and Schumpeterian patterns of innovation”, *Economic Journal*, 110, pp. 388-410.

BURT, R. (1992), “Structural holes: The social structure of competition”, Harvard University Press, Cambridge.

CASSI, L. and MORRISON, A. (2007), “Social networks and innovation: concepts, tools and recent empirical contributions”, *Dinamia WP 59/07*, ISCTE, Lisbon.

CASTELLACI, F. (2007), “Technological regimes and sectoral differences in productivity growth”, *Industrial and Corporate Change*, 16: 1105–1145.

CASTILLA, E., HWANG, H., GRANOVETTER, E. and GRANOVETTER, M. (2000), “Social networks in Silicon Valley”, in C.M. Lee, W.F. Miller, H. Rowen and M. Hancock (eds.) “The Silicon Valley Edge – A Habitat for Innovation and Entrepreneurship”, pp. 217-247, Stanford, Stanford University Press.

CHESBROUGH, H. and ROSENBLOOM, R.S. (2002), “The role of the business model in capturing value from innovation: evidence from Xerox Corporation's technology spin-off companies”, *Industrial and Corporate Change*, 11, pp. 529-555.

COHEN, W.M, NELSON, R.R. and WALSH, J.P. (2000), “Protecting their intellectual assets: appropriability conditions and why U.S. manufacturing firms patent (or not)”, National Bureau of Economic Research, WP No. 7522.

COLEMAN, J. (1988), “Social capital in the creation of human capital”, *American Journal of Sociology*, 94, pp. 95-120.

COLOMBO, M.G., GRILLI, L. and PIVA, E. (2006), “In search of complementary assets: The determinants of alliance formation of high-tech start-ups”, *Research Policy*, 35, pp. 1166–1199.

CORIAT, B., ORSI, F. and WEINSTEIN, O. (2003), “Does biotech reflect a new science-based innovation regime?”, *Industry and Innovation*, 10, pp. 231–253.

COSTA, C., FONTES, M. and HEITOR, M.V. (2004), “A methodological approach to the marketing process in the biotechnology-based”, *Industrial Marketing Management*, 33, pp. 403-418.

DAHL, M. and PEDERSEN, C. (2004), “Knowledge flows through informal contacts in industrial clusters: myth or reality?”, *Research Policy*, 33, pp. 1673-1686.

DE JONG, J.P.J. and MARSILI, O. (2006), “The fruit flies of innovations: A taxonomy of innovative small firms”, *Research Policy*, 35, pp. 213-229.

DOSI, G. (1982), “Technological paradigms and technological trajectories”, *Research Policy*, 11, pp. 147-162.

DOSI, G. (1988), “Sources, procedures and microeconomic effects of innovation”, *Journal of Economic Literature*, 26(3), pp. 1120-1171.

ELFRING, T. and HULSINK, W. (2003), “Networks in entrepreneurship: The case of high-technology firms”, *Small Business Economic*, 21, pp. 409-422.

EVANGELISTA, R. (2000), “Sectoral patterns of technological innovation in services”, *Economics of Innovation and New Technology*, 9(3), pp. 183-222.

EVANGELISTA, R. and MASTROSTEFANO, V. (2006), “Firm size, sectors and countries as sources of variety in innovation”, *Economics of Innovation and New Technology*, 15, pp. 247-270.

FONTES, M. (2005), “Distant networking: The knowledge acquisition strategies of 'out-cluster' biotechnology firms”, *European Planning Studies*, 13(6), pp. 899-920.

FREEL, M. and DE JONG, J. (2009), “Market novelty, competence-seeking and innovation networking”, *Technovation*, 29, pp. 873–884.

FREEMAN, L. (1978/79), “Centrality in Social Networks Conceptual Clarification”, *Social Networks*, 1, pp. 215-239.

FRENZ, M. and PREVEZER, M. (2010), “The impact of technological regimes on patterns of sustained and sporadic innovation activities in UK industries”, *Working Papers 33*, Queen Mary, University of London, School of Business and Management, Centre for Globalisation Research.

GANS, J. and STERN, S. (2003), “The Product Market and the Market for ‘Ideas’: Commercialisation Strategies for Technology Entrepreneurs”, *Research Policy* 32, PP. 333-50.

GIARRATANA, M.S. (2004), “The birth of a new industry: entry by start-ups and the drivers of firm growth. The case of the encryption software”, *Research Policy*, 33, pp. 787-806.

GILSING, V.A. and NOOTEBOOM, B. (2005), “Density and strength of ties in innovation networks: an analysis of multimedia and biotechnology”, Discussion Paper No 2005-41, Eindhoven Centre for Innovation Studies, Tilburg University.

GIULIANI, E. (2007), “The selective nature of knowledge networks in clusters: evidence from the wine Industry”, *Journal of Economic Geography*, 7, pp. 139-168.

GIULIANI, E. and BELL, M. (2005), “The micro-determinants of meso-level learning and innovation: evidence from a Chilean wine cluster”, *Research Policy*, 34, pp. 47-68.

GRANDI, A. and GRIMALDI, R. (2003), “Exploring the networking characteristics of new venture founding teams”, *Small Business Economics*, 21, pp. 329–341.

GRANOVETTER, M. (1973), “The strength of weak ties”, *American Journal of Sociology*, 78(6), pp. 1360–1380.

GREENE, W.H. (2011), “Econometric Analysis”, 7th Edition. Prentice Hall.

GREVE, A. and SALAFF, J.W. (2003), “Social networks and entrepreneurship”, *Entrepreneurship Theory and Practice*, 28, pp. 1-22.

GULATI, R. (1998), “Alliances and networks”, *Strategic Management Journal*, 19, pp. 293-317.

HAGEDOORN, J. (1993), “Understanding the rationale of strategic technology partnering: interorganizational modes of cooperation and sectoral differences”, *Strategic Management Journal*, 14, pp. 371-385.

HALL, B.H. (2005), “Exploring the patent explosion”, *The Journal of Technology Transfer*, 30, pp. 35-48.

HANNEMAN, R. and RIDDLE, M. (2005), "Introduction to social network methods", University of California, Riverside, CA.

HANSEN, M.T. (1999), "The search-transfer problem: the role of weak ties in sharing knowledge across organization studies", *Administrative Science Quarterly*, 44, pp. 82-111.

HARABI, N. (1995), "Appropriability of technical innovations. An empirical analysis", *Research Policy*, 24, pp. 981-992.

HICKS, D. and HEDGE, D. (2005), "Serial innovators in the markets for technology", *Research Policy*, 34, pp. 703-716.

HITE, J. and HESTERLY, W. (2001), "The evolution of firm networks: from emergence to early growth of the firm", *Strategic Management Journal*, 22, pp. 275-286.

HURMELINNA-LAUKKANEN, P. and PUUMALAINEN, K. (2007), "The nature and dynamics of appropriability – Strategies for appropriating returns on innovation", *R&D Management*, 37, pp. 95-112.

JAFFE, A.B., TRAJTENBERG, M. and HENDERSON, R. (1993), "Geographic localization and knowledge spillovers as evidenced by patent citations", *Quarterly Journal of Economics*, 108, pp. 577-598.

JOHANNISSON, B. (1998), "Personal networks in emerging knowledge-based firms: Spatial and functional patterns", *Entrepreneurship & Regional Development*, 10, pp. 297-312.

KIM, D.J. and KOGUT, B. (1996), "Technological platforms and diversification", *Organization Science*, 7, pp. 283-301.

KLEVORICK, A., LEVIN, R.C., NELSON, R.R. and WINTER, S.G. (1995), "On the sources and significance of interindustry differences in technological opportunities", *Research Policy*, 24, pp. 185-205.

KOGUT, B. and ZANDER, U. (1992), "Knowledge of the firm, combinative capabilities, and the replication of technology", *Organization Science*, 3, pp. 383-397.

KRATZER, J., GEMU, H.G. and LETTL, C. (2009), “Balancing creativity and time efficiency in multi-team R&D projects: the alignment of formal and informal networks”, *R&D Management*, 38(5), pp. 538-549.

KREINER, K. and SCHULTZ, M. (1993), “Informal collaboration in R&D. The formation of networks across organizations”, *Organization Studies*, 14(2), pp. 189-209.

LANE, P. and LUBATKIN, M. (1998), “Relative absorptive capacity and interorganizational learning”, *Strategic Management Journal*, 19(5), pp. 461-477.

LEIPONEN, A. and DREJER, I. (2007), “What exactly are technological regimes?”, *Research Policy*, 36, pp. 1221-1238.

LEVIN, R.C., KLEVORICK, A.K., NELSON, R.R., and WINTER, S.G. (1987), “Appropriating the returns from industrial research and development”, *Brookings Papers on Economic Activity*, 3, pp. 783–832.

LEVITTE, Y. M., BAGCHI-SEN, S. (2010), “Demographics, Innovative Outputs and Alliance Strategies of Canadian Biotech Firms”, *European Planning Studies*, 18, PP.669-690.

LIEBESKIND, J.P., OLIVER, A.L., ZUCKER, L. and BREWER, M. (1996), “Social networks, learning and flexibility: Sourcing scientific knowledge in new biotechnology firms”, *Organization Science*, 7, pp. 428- 443.

LIPPOLDT, D. and STRYSZOWSKI, P. (2009), “Innovation in the software sector”, OECD, Paris.

LISSONI, F. (2001), “Knowledge codification and the geography of innovation: The case of Brescia mechanical cluster”, *Research Policy*, 30(9), pp. 1479–1500.

LONG, J. S. (1997), “Regression Models for Categorical and Limited Dependent Variables”, Sage Publishing.

LOVAS, B. and SORENSON, O. (2008), “The mobilization of scarce resources”, in J.A. Baum and T. J. Rowley, “Advances in Strategic Management: Network Strategy”, 25, JAI Press, Amsterdam.

LOW, M.B. and ABRAHAMSON, E. (1997), "Movements, bandwagons and clones: Industry evolution and the entrepreneurial process", *Journal of Business Venturing*, 12, pp. 435-457.

LUNDEVALL, B.A. (1993), "Explaining interfirm cooperation and innovation. Limits of the transaction-cost approach", in G. Grabher (ed.), "The Embedded Firm. On the Socioeconomics of Industrial Networks", Routledge, London.

MALERBA, F. (2005), "Sectoral systems of innovation: A framework for linking innovation to the knowledge base, structure and dynamics of sectors", *Economics of Innovation and New Technology*, 14 (1-2), pp. 63-82.

MALERBA, F. (2006), "Innovation and the evolution of industries", *Journal of Evolutionary Economics*, 16, pp. 3-23.

MALERBA, F. and ORSENIGO, L. (1993), "Technological regimes and firm behaviour", *Industrial and Corporate Change*, 2, pp. 45-71.

MALERBA, F. and ORSENIGO, L. (1997), "Technological regimes and sectoral patterns of innovative activities", *Industrial and Corporate Change*, 6, pp.81-117.

MARSILI, O. (2002), "Technological regimes and sources of entrepreneurship", *Small Business Economics*, 19, pp.217-231.

MARSILI, O. and VERSPAGEN, B. (2002), "Technology and the dynamics of industrial structures: an empirical mapping of Dutch manufacturing", *Industrial and Corporate Change*, 11(4), pp. 791-815.

MASKELL, P. and MALMBERG, A. (1999), "Localised learning and industrial competitiveness", *Cambridge Journal of Economics*, 23, pp. 167-185.

MCEVILY, B. and ZAHEER, A. (1999), "Bridging ties: a source of firm heterogeneity in competitive capabilities", *Strategic Management Journal*, 20, pp. 1133-1156.

MCKELVEY, M. (2005), "What drives innovation processes in modern biotechnology and open source software?", *Innovation: Management, Policy & Practice*, February.

MCMILLAN, G., NARIN, F., DEEDS, D. (2000), “An analysis of the critical role of public science in innovation. The case of biotechnology”, *Research Policy*, 29(1), pp. 1-8.

MOENSTED, M. (2007), “Strategic networking in small high tech firms”, *International Entrepreneurship and Management Journal*, 3, pp. 15-27.

MOODYSSON, J., COENEN, L. and ASHEIM, B.T. (2008), “Explaining spatial patterns of innovation: Analytical and synthetic modes of knowledge creation in the Medicon Valley life-science cluster”, *Environment and Planning A*, 40, pp. 1040–1056.

MORRISON, A. and RABELLOTTI, R. (2009), “Knowledge and information networks in an Italian wine cluster”, *European Planning Studies*, 17(7), pp. 983-1006.

MURRAY, F. (2002), “Innovation as co-evolution of scientific and technological networks: exploring tissue engineering”, *Research Policy*, 31, pp. 1389-1403.

MURRAY, F. (2004), “The role of inventors in knowledge transfer: sharing in the laboratory life”, *Research Policy*, 33, pp. 643-659.

NESTA, L. and DIBIAGGIO, L. (2003), “Technology strategy and knowledge dynamics: The case of Biotech”, *Industry and Innovation*, 10, pp. 329-347.

OKAMURA, K. and VONORTAS, N. (2006), “European alliance and knowledge networks”, *Technology Analysis & Strategic Management*, 18, pp. 535-560.

ORSENIGO, L., PAMMOLLI, F. and RICCABONI, M. (2001), “Technological change and network dynamics. Lessons from the pharmaceutical industry”, *Research Policy*, 30, pp. 485-508.

OSTERGAARD, C. (2009), “Knowledge flows through social networks in a cluster: comparing University and industry links”, *Structural Change and Economic Dynamics*, 29, pp. 196-210.

OWEN-SMITH, J. and POWELL, W.W. (2004), “Knowledge networks as channels and conduits: The effects of spillovers in the Boston biotechnology”, *Organization Science*, 15(1), pp. 6-21.

OZMAN, M. (2009), “Inter-firm networks and innovation: a survey of literature”, *Economics of Innovation and New Technology*, 18 (1), pp. 39:67.

PALMBERG, C. (2001), “Tracing technological opportunities, patterns of innovation and competence requirements through micro data”, *Nelson & Winter Conference 2001*; Aalborg.

PAVITT, K. (1984), “Sectoral patterns of technical change: Towards a taxonomy and a theory”, *Research Policy*, 13, pp. 343-373.

PENEDER, M. (2010), “Technological regimes and the variety of innovation behaviour: Creating integrated taxonomies of firms and sectors”, *Research Policy*, 39(3), pp. 323-334

PISANO, G.P. and TEECE, D.J. (2007), “How to capture value from innovation: shaping intellectual property and industry architecture”, *California Management Review*, 50(1), pp. 278-296.

PLUM, O. and HASSINK, R. (2011), “Comparing knowledge networking in different knowledge bases in Germany”, *Papers in Regional Science*, 90(2), pp.355-372.

POWELL, W., KOPUT, K. and SMITH-DOERR, L. (1996), “Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology”, *Administrative Science Quarterly*, 41, pp. 116-145.

POWELL, W. and GRODAL, S. (2005), “Networks of innovators”, in J. Fagerberg, D. Mowery, and R. Nelson (eds.), “*The Oxford Handbook of Innovation*”, pp. 56-85, Oxford University Press, Oxford.

RAO, P.M. and KLEIN, J.A. (1994), “Growing importance of marketing strategies for the software industry”, *Industrial Marketing Management*, 23, pp. 29-37.

ROSENKOPF, L. and TUSHMAN, M. (1998), “The coevolution of community networks and technology: Lessons from the flight simulation industry”, *Industrial and Corporate Change*, 7, pp. 311-346.

ROTHAERMEL, F.T. (2002), “Technological discontinuities and interfirm cooperation: what determines a start-up’s attractiveness as alliance partner?”, *IEEE Transactions on Engineering Management*, 49, pp. 388-397.

SALAVISA, I., VIDEIRA, P. and SANTOS, F. (2009), “Entrepreneurship and social networks in IT sectors: the case of the software industry in Portugal”, *Journal of Innovation Economics*, 2009/2, pp. 15-39.

SAVIOTTI, P.P. (1998), “On the dynamics of appropriability of tacit and of codified knowledge”, *Research Policy*, 26, pp. 843-856.

SCHRADER, S. (1991), “Informal technological transfer between firms: cooperation through information trading”, *Research Policy*, 20, pp. 153-170.

SHANE, S. (2003), “A general theory of entrepreneurship: The individual-opportunity nexus”, Edward Elgar, Cheltenham.

SINGH, J. (2005), “Collaborative networks as determinants of knowledge diffusion patterns”, *Management Science*, 51(5), pp. 756-770.

SINGH, R.P. (2000), “Entrepreneurial opportunity recognition through social networks”, Garland, London.

SMITH-DOERR, L. and POWELL, W. (2005), “Networks and Economic Life” in N. Smelser and R. Swedberg (eds.), “The Handbook of Economic Sociology”, Princeton University Press.

SOUTARIS, V. (2002), “Technological trajectories as moderators of firm-level determinants of innovation”, *Research Policy*, 31, pp. 877-898.

SOUSA, C., FONTES, M. and VIDEIRA, P. (2011), “The role of entrepreneurs’ social networks in the creation and early development of biotechnology companies”, *International Journal of Entrepreneurship and Small Business*, 12(2), pp. 227-244.

STEINMUELLER, E. (2000), “Does information and communication technologies facilitate ‘codification’ of knowledge?”, *Industrial and Corporate Change*, 9, pp. 361-376.

- STUART, T. E., OZDEMIR, S. Z. and DING, W. W. (2007), “Vertical alliance networks: the case of university–biotechnology–pharmaceutical alliance chains”, *Research Policy*, 36, pp. 477–98.
- STUART, T.E. and SORENSON, O. (2003), “The geography of opportunity: spatial heterogeneity in founding rates and the performance of biotechnology firms”, *Research Policy*, 32, pp. 229-253.
- STUART, T.E., HOANG, H. and HYBELS, R. (1999), “Interorganizational endorsements and the performance of entrepreneurial ventures”, *Administrative Science Quarterly*, 44, pp. 315-349.
- SWANN, P. and PREVEZER, M. (1996), “A comparison of the dynamics of industrial clustering in computing and biotechnology”, *Research Policy*, 25, pp. 1139-1157.
- TEECE, D.J. (1986), “Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy”, *Research Policy*, 15, pp. 285-305.
- TIDD, J., BESSANT, J. and PAVITT, K. (1997), “Managing Innovation – Integrating Technological, Market and Organizational Change”, Wiley, Chichester.
- TRIPPL, M., TODTLING, F. and LENGAUER, L. (2009), “Knowledge sourcing beyond buzz and pipelines: evidence from the Vienna software sector”, *Economic Geography*, 85(4), pp. 443-462.
- UZZI, B. (1997), “Social structure and competition in interfirm networks: the paradox of embeddedness”, *Administrative Science Quarterly*, 42, pp. 35-67.
- VAN GEENHUIZEN, M. (2008), “Knowledge networks of young innovators in the urban economy: biotechnology as a case study”, *Entrepreneurship and Regional Development*, 20, pp. 161-183.
- VON HIPPEL, E. (1987), “Cooperation between rivals: informal know-how trading”, *Research Policy*, 16, pp. 291-302.

WASSERMAN, S. and FAUST, K. (1994), "Social network analysis. Methods and applications", Cambridge University Press, Cambridge.

WENGER, E. (1998), "Communities of practice and social learning systems", *Organization*, 7(2), pp. 225-246.

WETERINGS, A. and PONDS, R. (2009), "Do regional and non-regional knowledge flows differ? An empirical study on clustered firms in the Dutch life sciences and computing services industry", *Industry & Innovation*, 16 (1), pp. 11-31.

WINTER, S.G. (1984), "Schumpeterian competition in alternative technological regimes", *Journal of Economic Behavior and Organization*, 5, pp. 287-320.

YLI-RENKO, H., AUTIO, E. and SAPIENZA, H.J. (2001), "Social capital, knowledge acquisition, and knowledge exploitation in young technology-based firms", *Strategic Management Journal*, 22, pp. 587-613.

ZHAO, L. and ARAM, J.D. (1995), "Networking and growth of young technology-intensive ventures in China", *Journal of Business Venturing*, 10(5), pp. 349-370.

ZUCKER, L., DARBY, M. and BREWER, M. (1998), "Intellectual human capital and the birth of U.S. biotechnology enterprises", *American Economic Review*, 88(1), pp. 290–306.

ZUCKER, L.G., DARBY, M.R. and ARMSTRONG, J.S. (2002), "Commercializing knowledge: University science, knowledge capture, and firm performance in biotechnology", *Management Science*, 48, pp. 138–153.