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The dynamic effects of knowledge base complexity on Schumpeterian patterns of innovation: A case study of the upstream petroleum industry

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Abstract

This paper proposes that shifts in sectorial patterns of innovation over the industry?s lifecycle partly depend upon the dynamics of knowledge base complexity. Knowledge base complexity is considered as one of the important dimension of technological regimes which define sectorial knowledge environment and shape the sectorial patterns of innovation. Although the relationship between technological regimes and sectorial patterns of innovation has been confirmed in a series of empirical studies, most of them relied on comparative cross-section mode of analysis. As a result, technological regimes are conceived as an invariant variable over time which differentiates patterns of innovation across sectors. The novelty of this study consists of a dynamic approach to technological regimes in which concentrates on changing patterns of innovation in the same industry over time. We focus on the dynamics of knowledge complexity in upstream petroleum industry. We find that an increase in knowledge base complexity tends to alter the mode of Schumpeterian patterns of innovation from Mark I to Mark II. However, changes in technological opportunities do not alter the mode of Schumpeterian patterns of innovation, albeit they can influence the intensity of the existing pattern.

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Abstract: This paper proposes that shifts in sectorial patterns of innovation over the industry's lifecycle partly depend upon the dynamics of knowledge base complexity. Knowledge base complexity is considered as one of the important dimensions of technological regimes which define sectorial knowledge environment and shape the sectorial patterns of innovation. Although the relationship between technological regimes and sectorial patterns of innovation has been confirmed in a series of empirical studies, most of them relied on comparative cross-section mode of analysis. As a result, technological regimes are conceived as an invariant variable over time which differentiates patterns of innovation across sectors. The novelty of this study consists of a dynamic approach to technological regimes which concentrates on changing patterns of innovation within the same industry over time. We focus on the dynamics of knowledge complexity in the upstream petroleum industry. We find that an increase in knowledge base complexity tends to alter the mode of Schumpeterian patterns of innovation from Mark I to Mark II. However, changes in technological opportunities do not alter the mode of Schumpeterian patterns of innovation, albeit they can influence the intensity of the existing pattern

Keywords: Schumpeterian patterns of innovation, technological regimes, knowledge base complexity, and upstream petroleum industry.

1. Introduction: Schumpeterian patterns of innovation

In the Schumpeterian tradition, the distinction between Mark I and II has proved a useful analytical tool to distinguish different sectorial patterns of innovation among different industrial sectors. According to Malerba and Orsenigo (1996; 1997) the fundamental question is "how and why innovation differs across sectors?" Malerba (2004, p.380). This article asks whether the Schumpeterian dichotomy is a useful analytical tool to understand how and why innovation differs in the same sector over time. The patterns of innovation and knowledge accumulation in one industry gradually changes as a result of technical change and the associated division of labour. As industries progress, their knowledge base can move to higher orders of complexity which involves both higher differentiation and greater integration capacity. This may create a shift in the Schumpeterian pattern of innovation; we study these dynamics using empirical evidence from the upstream petroleum industry.

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Schumpeter Mark I is characterized by creative destruction whereby new firms play a major role in innovative activities and barriers to entry in technological activities are low. In contrast, creative accumulation is the main characteristic of Schumpeter Mark II. Large established firms play major role in technological activities. It is challenging for new small innovators to enter into these industries. These two types are also labelled as widening and deepening by other scholars who tried to find empirical verifications for these two major patterns of innovation Malerba and Orsenigo (1997).

In a series of investigations, Malerba and Orsenigo (1995, 1996, and 1997) found empirical support for the two archetypical patterns based on four indicators: 1-Concentration and asymmetries (captured by the Herfindahl index) of innovative activities within firms, 2-innovation size of the firms, 3-stability of the ranking of innovators over time, and 4-relative share of new innovators in comparison with the incumbents. The statistical analysis of these indicators produced quite reliable results, finding a meaningful relationship observed within these variables on the one hand, and distinguishing two archetypical Schumpeterian patterns of innovation on the other (Malerba and Orsenigo, 1995; 1996; 1997; Breschi et al., 2000; Malerba, 2007). Malerba (2005) claims that based on an industry life-cycle (ILC) view, Schumpeterian Mark I patterns can turn into Mark II when the sector tends to mature, technological change starts to follow existing trajectories, and economies of scales, barriers to entry and financial resources shape the competitive race.

Although this line of research achieved very important results, the findings suffer from two limitations. First, the methodology used does not allow for the observation of variations within technological classes and industries, because the analysis relies on aggregated data. Rather it forces every technological class or industry to be dropped just into one of the archetypical patterns of innovation. Second, the methodology employed does not allow for the observation of temporal variation in sectorial patterns of innovation within industries, simply because the time dimension is removed. So while it is widely accepted that patterns of innovation change over time, such observation is based on average behaviour over time for every single technology class (Malerba and Orsenigo, 1996).

These limitations and assumptions have been partly addressed by more recent studies. For example, Corrocher et al. (2007) observed the co-existence of both Schumpeterian patterns of innovation in ICT industry. Grebel et al (2007) also provided similar evidence, arguing the co-existence of large diversified and new technology firms within innovation networks in knowledge intensive industries like biotechnology and telecommunication. They actually emphasised the critical function of innovation networks which combine both “entrepreneurial and managerial routs to innovation or as Schumpeter Mark I and II” (Grebel et al, 2007 p.66).

With regard to lack of a dynamic approach, Malerba and Orsenigo (1996) highlighted the importance inter-temporal shifts in sectorial patterns of innovation as an under-researched topic. In the next work, Malerba and Orsenigo elaborated more, acknowledging explicitly the possibility of change in the nature of technological regimes over the course of time:

> "Some of these features of knowledge may change during the evolution of a specific sector or technology (degree of codification, independence, and complexity)" (Malerba and Orsenigo 1997, p. 97).

Malerba and Orsenigo (2000) argue that discussing the relevant dimensions of knowledge is a key requirement to develop an in-depth understanding of the relationship between innovative dynamics within sectors and industrial evolution. Later in a review article about innovation and industry evolution, Malerba (2006, p. 14-15) added that "change in knowledge and knowledge base… goes to the heart of the evolution of the industries and of the factors affecting the change in industrial structure" (emphasis added). However, such change was conceived as very difficult to identify over significant periods of time even in the case of single sectors, let alone the identification of regularities across a range of industrial sectors.

The notion of technological regimes has proved powerful in explaining inter-sectorial differences in sectorial patterns of innovation. The question that remains open is whether the same is true for inter-temporal comparisons. Given the introduction of extensive technological innovation to current industries and its impact of complexity of sectorial knowledge, we explore the dynamics of technological opportunities and knowledge base complexity, among other dimensions of technological regimes. This mode of analysis requires a dynamic reading of the concept of technological regimes, not to be considered as an invariant variable in the long run. We examine the co-evolution between dynamics of technological regimes and Schumpeterian patterns of innovation, using evidence from the upstream petroleum industry. The choice of focusing on the upstream petroleum industry is due to the documented patterns of change in the knowledge base and the industry evolution.

Section 2 present a dynamic reading of the concept of technological regimes and explore the knowledge gap in the literature. We explore the changes in technological regimes of the upstream petroleum industry, focusing on dynamics of technological opportunities and knowledge base complexity. According to the observed patterns of change in technological regimes in section 3, in section 4 we define our research question and hypothesis. Our effort in section 5 is to capture the dynamics of Schumpeterian patterns of innovation in the upstream petroleum industry in order to examine the research hypothesis. In the section 6, we discuss how shifts in Schumpeterian patterns of innovation can be explained based on dynamics of knowledge base complexity. Section 7 summarises our findings and concludes.

2. Technological regimes in dynamic perspective

In this section we describe the literature background of the concept of technological regimes, exploring its dynamic a key but neglected aspect in the analysis of structural change and industry evolution. The notion of technological regimes was firstly introduced by Nelson and Winter (1982), referring to the knowledge environment in which firms operate, or in which their problem-solving activities take place (Winter, 1984). More recently, four building blocks were identified, including technological opportunity, the appropriability of innovations, their cumulativeness, and knowledge base properties (Breschi et al., 2000; Breschi and Malerba, 2000). The properties of the knowledge base which shape innovative activities constitute a synthetic construct encompassing the degree of specificity, tacitness, complexity and independence (Breschi et al., 2000).

Technological opportunities refer to the likelihood of innovation in a particular sector resulting from a given amount of money invested in search processes. Over the ILC, technological opportunities may significantly change suggesting it as a dynamic concept. The standard ILC model assumes that opportunity conditions are depleted when industries get mature (Klepper, 1996). However, some empirical statistical analysis (McGahan and Silverman, 2001), case studies in mature industries (Acha and Brusoni; 2005) and research on innovation in low-tech industries (Robertson et al., 2009 & 2007; Mendonça, 2009; Hirsch-Kreinsen, et al., 2006; Von Tunzelmann and Acha; 2005) show that this is not necessarily the case. In other words, no simple relationship between industry life cycle and technological opportunities could be established.

Appropriability of innovations reflects the possibility of protection of innovation from imitation through various strategies to pay off the costs and earn profits. Companies employ different range of strategies to capture the benefits of their innovations such as patent or other intellectual properties, vertical integration and control of complementary assets, or even shaping the ‘industry architecture’ (Teece, 1986; Levin et al.; 1987; Jacobides et al. 2006; Pisano and Teece, 2007). This dimension is also a dynamic concept, in that it is a function of the firm’s strategies (like choice of patent or secrecy), their environment (such as patent laws and regulations), and nature of knowledge to be protected (such as tacitness).

Cumulativeness captures the degree to which today's available knowledge and innovative activities form the foundation of future innovations, creating some kind of path dependency in the technological trajectory. The degree of cumulativeness may change over time, which has been documented by works such as Tushman and Anderson, (1986), Bergek, et al. (2013), and Dosi (1982).

Knowledge base properties: The degree of specificity, tacitness, independence and complexity are the main properties of the knowledge base which are discussed in the literature of technological regimes (Breschi and Malerba, 2000). Specificity refers to the scope of applications of particular knowledge domain. Tacitness refers to the extent to which knowledge is not articulated in standard formats such as blue prints. Degree of independence which is often defined versus systemic knowledge base refers to the extent that relevant knowledge to the innovative activities could be easily isolated.

Like other dimensions of technological regimes, these properties of the knowledge base could also change over time as a result of new application, inter-industry knowledge flows, codification practices, new instrumentation and computational capabilities (Arora and Gambardella, 1994) or facilitation of ICT (Steinmueller, 2000).

Changes in one or more of these dimensions of technological regime are likely to have important implications for sectorial patterns of innovation (Malerba and Orsenigo, 1995; 1996; 1997; Malerba, 2007). We test this intuition in the upstream petroleum industry with particular focus on the dynamics of knowledge base complexity. From the perspective of literature on technological regimes (Malerba and Orsenigo, 1997; Breschi and Malerba, 2000), a knowledge base is defined as complex if (a) it involves integration and combination of different scientific and technological disciplines and (b) requires a variety of competences (such as R&D, design and engineering, manufacturing, production and marketing) for innovative activities. While technological opportunities, appropriability and cumulativeness of knowledge are addressed in previous research (Malerba and Orsenigo, 1995; 1996; 1997; Breschi et al., 2000) so far the role of knowledge base complexity has not been properly addressed, with the noticeable exception of a few qualitative case studies: the analysis of the footwear industry has shown how transformation of the traditional knowledge base of the sector to a complex system created a more complex organization of innovation (Vale and Caldeira, 2008); similar structural change is observed in the salmon farming industry in Chile (Iizuka, 2009).

This article proposes a quantitative method for exploration of the dynamics of knowledge base complexity and Schumpeterian patterns of innovation and the possible links between the two. We examine whether statistical quantitative methods which are employed in inter-sectorial studies could also reveal the association between dynamics of knowledge base complexity and patterns of innovation.

3. Dynamics of technological regimes in the upstream petroleum industry: measuring innovation trends and knowledge complexity.

In the previous section, we argued different dimensions of technological regimes could change over time leading to a transformation of sectorial patterns of innovation. In this section, we empirically examine this idea in the upstream petroleum industry, focusing on changes in technological opportunities and knowledge base complexity.

* * *

To begin with, we analyze the transformations of sectorial innovation systems in upstream petroleum by using the Derwent Innovating Index, a patent database which classifies all upstream petroleum industry patents in class H01. This class covers exploration, drilling, well services and stimulations, production and their sub segments of the upstream petroleum industry. In order to avoid double counting, we rely on the records of Derwent patent families which group similar inventions registered in different territories. Patent counts are used as a proxy to capture of dynamics of innovative performance of the sector. Patent data is the only rigorously classified information about technological innovation covering both long time periods and a wide range of countries. The advantages and limitations of patent data for the analysis of innovative activities is a widely discussed issue in the literature. It is particularly important to consider the limitations and disadvantages such as systematic biases in the data which may produce distorted results, if they are not treated properly. The main disadvantages include (Pavitt, K., 1985; Griliches, Z., 1990; OECD, 2009):

- Not all inventions are legally patentable. The classic example is software which is often protected by copyright. Moreover, the patenting scope may differ from one country to another depending on their particular patent law.
- Although some international agreements have become effective, in the end patents are binding within national territories. Because of different institutional structures in different countries which affect the length, time and effectiveness of protection, the inventor's interest may differ in terms of the countries where they seek protection.

- Patents are not the only or even the major tool to protect inventions. There are alternatives such as lead time and industrial secrecy.
- The patenting propensity is different among firms and industries. For some industries, a patent is a major competitive tool, while for some other industries it is not.

While patents are only imperfect measures of innovation order, nonetheless we believe that results of this study are not seriously affected. This is because almost all of the conclusions in this study are drawn based on the analysis of the trends rather than actual levels of the suggested variables. Therefore, we expect imperfections to shift levels up or down without influential impact on the trends.

3.1. The trend of technological opportunities

Following previous studies - such as Andersen (2005); Park and Lee (2006) and Fai(2007), we use patenting growth rate to capture dynamics of technological opportunities in the upstream petroleum industry. This measure is best understood in relative terms when inter-sectorial or inter-temporal comparisons are analyzed. We employ variation in patenting rate to examine how technological opportunities change over time. This kind of analysis could contribute to the understanding of both sources of variance in technological opportunities as well as its impact on industry performance measures such as R&D intensity and productivity (Klevorick et al., 1995).

Figure 1 presents the innovation trend in the upstream petroleum industry according to the number of patent applications in the US Patent Office (solid line). The dash-line shows the trend of total patenting in USPTO at 1% scale to control for the changes in the overall level of patenting. That is to examine whether observed dynamics of innovation is a reflection of technology push from other sectors, or the result of internal mechanisms within the upstream petroleum industry.

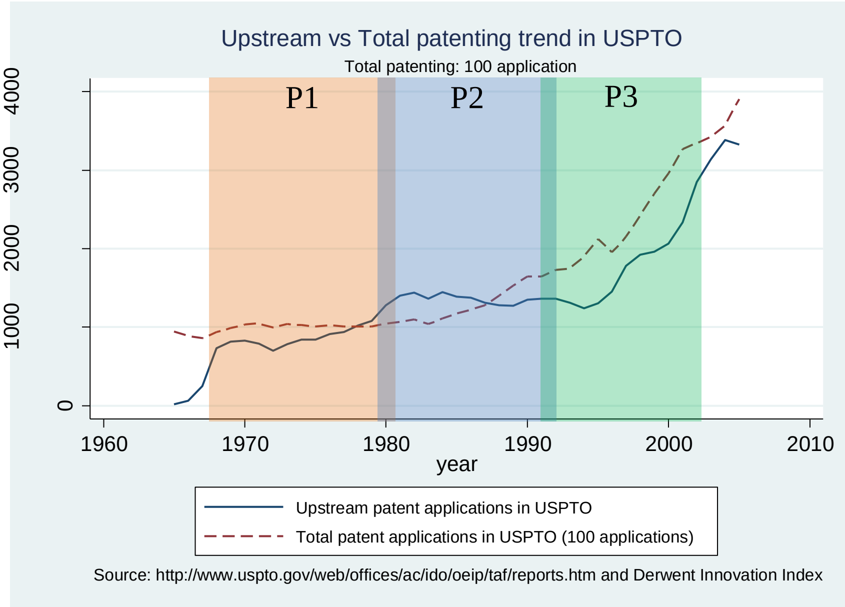
According to figure 1, the dynamics of innovation in the upstream petroleum industry presents three distinct periods over the last four decades. From the early 1970s until the mid-1980s, we observe a growing trend where the number of US patent applications almost doubled from about 700 per year in 1970 to about 1450 in 1984 (p1). The second period runs from 1984 to 1994, with a negative trend in innovation (p2). Third period begins in 1995 when the industry grows and shows a high propensity to innovate (p3).

The first period corresponds to the first and second oil shocks when oil prices were very high and worries of oil scarcity dominant. These two factors provided both powerful motives for upstream R&D investment. The aim was to open up more challenging reservoirs in harsh locations and the key was technology. These technological efforts were enormously successful to bring down exploration and production (E&P) costs and increasing reserve replacement ratios. The stable trend of total patenting in this period suggests that the rise of innovation is not attributable to this trend and should be explained according to upstream industry-specific factors.

This technological progress consequently led to excessive supply, pushing down oil prices for more than one and half decades. This self-correcting mechanism brought the upstream industry into the second period when patenting took a negative trend from the mid-1980s to the mid-1990s. This negative feedback loop could be seen as a long term and indirect impact of oil prices on innovation in the sector.

The second period shows about a 15% decline in upstream innovation while total patent application moves in the opposite direction expressing more than 70% growth over that period. This suggests that low oil prices acted as a disincentive for innovation, although total patenting was growing fast. In other words, when the industry is stagnating, the availability of technological opportunities from other industries cannot drive innovation.

Figure 1 The number of US patent applications over time



The third period is more complicated to analyze. While there is no large change in oil prices until 2002, nor technology-push trend (dash line in the figure 1) compared to the second period, the innovation performance of the industry has dramatically increased. The number of patent applications for upstream petroleum industry grew from about 1250 in 1994 to 3350 in

2005 experiencing growth of 170%, so that period saw an explosion of the search space for new technologies. While oil prices stayed low for most of this period. In spite of low oil prices, the innovation trend in upstream petroleum took a sharp onward trend after 1994, at least 6 year before rising oil prices. The key question is: what are the factors responsible for such a radical shift?

Several possible complementary explanations could be suggested for this innovation jump. At first glance, this is partly the result of technology push. As is evident from figure 1, patent applications for the entire industry increased from about 19,000 in 1994 to more than 39,000 in 2005 showing almost 105% growth, meaning 35% more than its growth rate in the second period. Although this trend seems acceptable as part of the answer, we think it is not sufficient for explaining the more pronounced shift in upstream innovation, especially if one compares the negative 15% growth rate in second period with positive 170% growth over the third period.

Our interpretation of the historical context suggests that a combination of demand side factors and industry architecture contributed to the dramatic change. The emergence of a demand for 'qualitatively' different innovation is partly responsible for the recent technological revolution of the industry. For example, the cost of finding and lifting oil which had a downward trend for about 15 years began to rise since 1995 (U.S. EIA, 2011). This signals that oil extraction is an increasingly challenging business. The nature of services, equipment, design and engineering in upstream projects should be adapted to geological location and geophysical characteristics of the reservoir such as the shape, size, temperature, and type of rocks. As time goes by, easy oil both in terms of the location and other characteristics is depleted and companies look for more difficult less-accessible locations and more challenging types of material to extract. Advanced and complex technology became a matter of survival, not just a tool for higher profits (U.S. EIA, 2011).

Nonetheless, the available industry architecture was mostly formed from operators and specialized service companies (Barreau 2002), which made it difficult to cope with new technological imperatives of the sector. Given low oil prices and limited resources for innovation, more efficient industry architecture was required to increase the productivity of the innovation system to give birth to new technologies at a higher pace. The emergence of new large integrated service companies represented a key factor in the rise of productivity in the innovation system. Larger scale mergers and acquisitions (M&A) activities moved the sector to a more concentrated industry structure which according to Teece and Armour

(1976) – made this industry more innovative. This systemic analysis suggests that reconfiguration of industry architecture was an organizational industry-wide response to the new technological requirements. This industry restructuring enabled the sector to express a surge in innovation trend, in spite of continued low oil prices. Overall, the service intensity of E&P activities and their knowledge content have significantly increased over time, which led Surya Rajan of IHS Cambridge Energy Research Associates to observe that:

> "If all technological innovations produced by the oil and gas industry were added up, they would probably rival NASA's space program or the Industrial Revolution." (Rajan, 2011. p. 11)

3.2. Knowledge base complexity

The concept of complexity has several distinctive types and definitions. The main concern of scholars writing on complexity (Wang and von Tunzelmann, 2000; Antonelli, 2011) is the volume of interdependencies and degree of interaction between elements of a system. For example Patel and Pavitt (1997) implicitly take this view and Sorenson and Rivkin (2006) directly refer to this dimension of complexity. This specific notion of knowledge complexity is present when "the opportunities to generate new knowledge are conditional on the identification and integration of the diverse bits of complementary knowledge that are inputs into the knowledge production process" (Antonelli, 2003, p.507). To say that this kind of complexity contributes to shape industrial dynamics means that the recombination of both pre-existing and new bits of knowledge is key for the generation of new knowledge and introduction of systemic innovations (Chesbrough and Teece, 1996).

The complementarity between bits of knowledge is the source of recombination and creation of this type of complexity. Knowledge indivisibility is the outcome of this process where systemic knowledge serves new functions which are not achievable by individual bits of knowledge. In sectors with high levels of this type of complexity, effective production and competitiveness requires access and control of a diverse range of knowledge on the one hand, and integrative coordination capability on the other. Successful innovation is not possible without full understanding of the compatibilities and complementarities of diverse ranges of technologies (Antonelli, 2003). Because the source of this complexity is often systemic innovation (Chesbrough and Teece, 1996), we label this type of complexity as systemic complexity.

3.2.1. Measurement of knowledge base complexity

Proxies to measure complexity should consider the links and interactions between different elements of the knowledge base and capture the recombinant nature of knowledge and its systemic complexity. In order to measure systemic complexity, the network representation of the knowledge base is very relevant. According to this view (Saviotti, 2009 and2011; Krafft, 2011), the knowledge base has a co-relational structure comprised of nodes and links between these nodes. In this view, nodes are technology classes and links represent relationships between technologies connecting nodes together. The measure of systemic complexity should consider the connectivity and the relationships between technologies or the structure of relationships between different knowledge domains. The dynamics of complexity are understood from changes in the pattern and strength of linkages and interactions between the nodes.

Systemic complexity or network connectivity may change as a result of formation of new ties between un-connected nodes or a stronger relationship between connected nodes. It also may change when isolated nodes appear or connected nodes are disconnected. The main advantage of network analysis indicators is that they consider knowledge as an integrated system in which both the building blocks of the system (nodes) and their interactions (ties) are investigated at the same time. This enables us to monitor how knowledge structure changes over time when new technologies emerge, diffuse and are integrated in the system or the old ones expire, are abandoned or disconnected from the knowledge base (Krafft et al., 2011).

Social Network Analysis (SNA) has a powerful toolbox to characterize the connectivity of the network. A matrix of co-occurrence of technological classes is formed to represent the knowledge network where the value of each cell is the number of inventions that two technological classes appeared together (Krafft et al., 2011). In other words, the more two technologies are jointed, the higher their connectivity. Among various measures available to describe the network connectivity and structure of the knowledge base, network density is one of the popular indexes. It describes the general level of linkages to nodes of a graph, defined as the total number of links as a proportion of the possible number of links between nodes. However the weakness of this measure is that it does not consider the strength of the nodes and links, and treats weak and strong links equally (Krafft, 2011). From previous research, we know that distribution of the links is highly unequal. A few nodes are very central and highly connected, while many others have very weak linkages or are isolated (Saviotti, 2009, 2011).

The degree of a node is used as one of the centrality measures, describing how strong is the level of connectivity of a node (Krafft, 2011). Formally, the following equation expresses the measure of degree centrality (DC):

$$DC_n = \sum_{i \in N \neq n} l_{ni}$$

Where **n** represents the nodes and **l** represent the links.

The DC is defined as the number of links of one node with other nodes of the network. Because this measure is affected by the network size, it is often divided by its maximum value to provide a normalized proxy (Krafft, 2011), as the following equation shows:

$$NDC_n = DC_n / (N - 1)$$

This normalization allows for comparability of the degree centrality over time and analysis of dynamics of systemic complexity, because the size of the knowledge network changes over time. DC characterises a single node, not the network. In order to create a measure of connectivity at the level of a network, we rely on the average of the degree centrality of all nodes of the network. However, following (Krafft, 2011), we used the average measure of degree centrality, weighted by relative frequency. This takes into account the highly unequal strength of the nodes, giving higher weights to important technological classes. Accordingly, the measure of systemic complexity of the knowledge base is weighted average degree centrality (WADC), as follows:

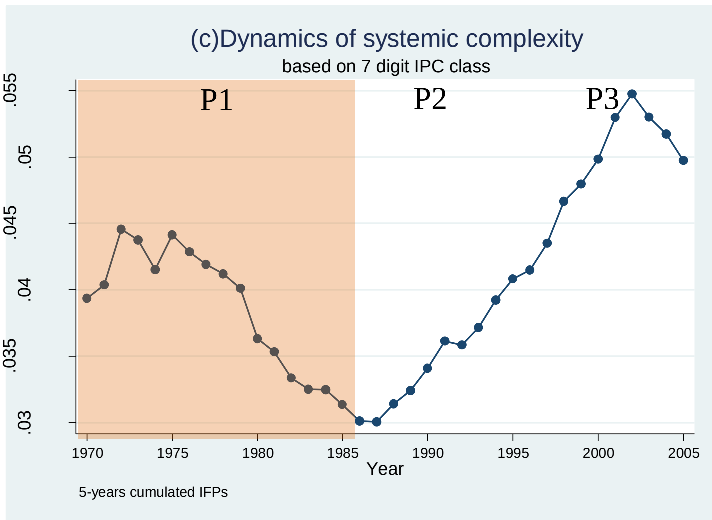
$$WADC = \sum_{n} [NDC_n * (P_n / \sum_{n} P_n)]$$

When the speed of formation new nodes outweighs the formation of links, the network becomes less connected and systemic complexity decreases (WADC decreases). In contrast, when the formation of new links is stronger than appearance of new nodes in the knowledge network, network connectively increases (Saviotti, 2011), signalling the rise of systemic complexity (WADC increases).

3.2.2. The dynamics of knowledge base complexity

The dynamics of knowledge base complexity in the upstream petroleum industry are presented in figure 2 using the WADC measure. The trend of systemic complexity over most of p1 takes a downward trend. As suggested by Saviotti (2011), it could be explained by higher rate of creation of new nodes, compared to new links between new and existing nodes. When new promising technological fields are explored, it takes some time for the innovators to understand the complementarity and the relationships between new and existing knowledge domains. The high technical risks involved in new knowledge domains may also prevent innovators from exploring possible complementarities and productive links, before emergence of a relatively clear picture of the trajectory and potential of the new technologies. We expect the emergence of novelty first to create new but poorly connected nodes, and therefore temporarily reduce the connectivity of the knowledge network (Saviotti, 2011). The first period in the upstream petroleum industry is the manifestation of this proposition. Emergence of new but poorly connected nodes increases the technological variety of the knowledge base, while also reducing its connectivity and total level of systemic complexity.

Figure 2: Dynamics of the three dimensions of knowledge base complexity in the upstream petroleum industry



As predicted by the knowledge network theory, the situation began to change when the direction of systemic complexity reversed in early p2, experiencing the rise of connectivity of the knowledge network. This could be explained by the diffusion and establishment of new technological fields explored in p1, when the rate of creation of new links overtakes the rate of emergence of new nodes. It does not imply that the emergence of new technological domains stopped; however their relative size became negligible compared to the established technological fields. By the end of p1 and during p2, the most promising fields which involve the highest technological opportunities gradually become known to industry participants.

Following Krafft et al. (2009, 2011), one could argue that search strategies gradually became organized rather than being random. The explorative behaviours were gradually replaced by exploitative strategies applied in the most productive technological areas. Innovators increasingly innovate more within technological classes which proved promising and fruitful, rather than spreading their R&D investment across many fields.

As mentioned earlier, systemic complexity matters where strong complementarities are discovered. This is why recent accounts in the theory of knowledge tend to describe it as a 'co-relational' entity (Saviotti, 2004, 2007) where different concepts create knowledge if, and only if, joined together. Therefore, generation of new knowledge in these conditions requires full understanding of the interdependencies and access to a divergent range of complementary pieces. When the processes of systemic complexity are dominant, the knowledge base of the industry is not developed just by accumulation of knowledge in existing knowledge domains or simple addition of new technical domains to existing ones, but through interactions and recombinations between existing and new technologies.

Systemic complexity is considered low when the knowledge base is relatively divisible and decomposable into pieces, and interdependencies are not well defined. In contrast, systemic complexity is considered high when the relationships between different technologies are relatively strong and stable. The interdependencies are defined and synergies and complementarities between technologies are discovered.

When an industry is in its early stages of the life cycle or after a large scale discontinuity, the knowledge complexity tends to be low. This is because, the most fruitful links and interactions have not still been explored and companies are searching to find out how the combination of different knowledge domains could create value. The decline of network connectivity over p1 illustrates a reduction of systemic complexity in this period, resulting from the emergence of new but unconnected technologies.

On the other hand, we expect higher systemic complexity when an industry matures. When new technologies and new forms of division of labour are established and their complementarities are explored, companies could generate new knowledge through recombination processes (Saviotti 2011). This could be a more productive knowledge generation process, because new knowledge is the outcome of the combination of existing knowledge. As a result of this strong emergent complementariness, the knowledge base of the sector is not easily divisible or decomposable and systemic complexity becomes increasingly high. The rise of knowledge network connectivity after early p2 suggests increasing systemic complexity of the upstream petroleum industry in this phase.

The high complementarity and systemic complexity increases investment returns on innovation, yet it increases barriers to entry for latecomers. Regarding knowledge complexity, the “larger the number of the bits of knowledge that can be recombined, the larger is the chances of generating new relevant knowledge” (Antonelli, 2003 p. 598). However, the dominance of systemic complexity after early p2 introduces important challenges and implications for latecomers. It is by definition more to the advantage of those who possesses or have access to the knowledge components, and against those who miss one or more of the critical components. In terms of the knowledge network, it is advantageous to those who occupy central positions in the knowledge networks having lots of connections, compared to marginal players.

4. Research question and hypothesis

Our central aim is to examine the relationship between dynamics of knowledge base complexity and sectorial patterns of innovation in the upstream petroleum industry. We ask:

What is the relationship between the dynamics of sectorial patterns of innovation and technological complexity?

We observe that over p1, systemic complexity is decreasing. In this phase, the sector is mostly in its random search period and exploration strategy is dominant. Because the structure of the knowledge base is changing and is not yet established, both cognitive barriers to entry and the degree of cumulativeness are relatively low. This situation also implies a low level of appropriability because the possibility of knowledge spill-overs is relatively high.

The complementarities between new and old knowledge domains have not been fully explored and the recombination process and knowledge linkages are not effective. In terms of knowledge network, poorly connected nodes emerge. As a result, access to a wide range of complementary knowledge is not necessary for the innovation process in this stage. Therefore we expect an increasing role for small and new companies relative to the role of big and established companies (or otherwise knowledge integrators) in the organization of innovation processes. In short, we expect the sector to move towards a Schumpeter Mark I mode.

In contrast, we observed that progressively during part p2 and throughoutp3, systemic complexity expresses a relatively sharp rising trend. As explained in section 3, when systemic complexity increases, the sector moves towards a more organized search period and exploitative strategies are pervasive (Krafft et al., 2011). Core technological domains are realized, technological trajectories are relatively clear and many productive complementarities and technical interdependencies are explored by industry participants. Innovative companies which connect and integrate different bits of knowledge can benefit from economy of scale and scope in knowledge generation and utilization processes. Cognitive barriers for small specialised companies are relatively higher, because successful innovation involves combination and recombination of various knowledge domains creating higher levels of cumulativeness.

In addition, increasing returns stemming from complementarities and fungeability of knowledge (Antonelli, 2003) favours big technologically diversified companies. As a result of the wider cumulativeness and higher appropriability mechanisms which emerge, more knowledgeable companies are expected to be better placed to benefit from cross-fertilization between different knowledge domains and their wide range of applications. The entry barriers for new companies will be higher and growth opportunities for small ones are limited. As a result, it is reasonable to expect that the sector becomes similar to or moves towards a Schumpeter Mark II mode.

Based on this analytical framework, we formulate the following hypothesis:
H1: The sector will move towards Schumpeter Mark I over p1 when systemic complexity is decreasing. We also expect a shift towards Schumpeter Mark II after early p2 when systemic complexity increases.

5. Dynamics of Schumpeterian patterns of innovation in upstream petroleum

In this section, we analyze the sectorial pattern of innovation. Following the extant literature (Malerba and Orsenigo, 1996; 1997; Breschi et al., 2000), we use a set of variables to examine whether the sector is moving towards Schumpeter I over p1 and shifts towards Schumpeter II after early p2, as predicted by H1. Although we use a similar set of variables, there is a fundamental difference between this study and previous research. These variables are normally used to distinguish different patterns of innovation in inter-sectorial studies. However, we employ them in an inter-temporal mode of analysis to explore the shift of sectorial patterns of innovation over time and within the same industrial sector.

Four indicators selected for the analysis of the dynamics of sectorial patterns of innovation are based on previous studies (Malerba and Orsenigo, 1996; 1997; Breschi et al., 2000). They are: concentration of innovative activities (C); the number of innovative firms (F); share of new entries (NE) to the innovation system in terms of the proportion of patents registered by new innovators; and, stability of the ranking of innovative firms (STR). We did not include the last indicator in our empirical analysis, as this did not produce robust results. This is perhaps due to strong structural change in this industry which makes this measure unreliable.

Although the variables of this inter-temporal research are similar to previous cross-sectorial studies, their operational correspondence with archetypical Schumpeterian patterns of innovation is interpreted differently. Due to dynamic nature of the analysis, we are interested more in the variables' trends, than in their values in cross-sectional designs. In other words, our interpretation is performed based on relative change of the variables over time.

Accordingly, positive or negative changes in these four variables will show toward which archetypical Schumpeterian patterns of innovation the industry is moving, that is they are moving closer to a typical Mark I or to a typical Mark II type. Table 1 summarizes the operational account of archetypical Schumpeterian patterns of innovation and the direction of the variables over time that we expect to observe in each typical mode. The Schumpeter Mark I sector is relatively open to the entrance of new or small firms. Therefore, we expect that over time, new firm entry and the number of innovating firms will increase, and as a result the concentration of innovative activities will decrease. This implies the relative low stability of the ranking of innovators, because new or small innovators have the opportunity to challenge the position of top innovators.

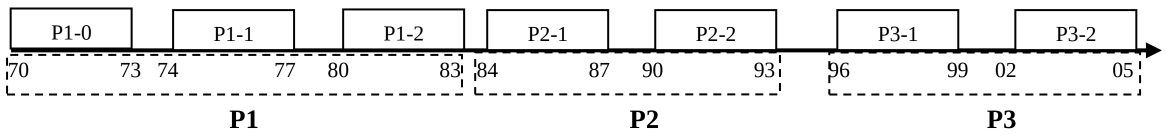
Table 1: Archetypical Schumpeterian patterns of innovation in dynamic perspective

Schumpeterian patterns of innovation	Schumpeter Mark I Widening	Schumpeter Mark II Deepening
Concentration (C)	↓	↑
Number of firms (F)	↑	↓ -
Entry of new firms (NE)	↑	↓
Stability of ranking (STR)	L	H
↓ decrease; ↑ increase; - stable; L: low; H: high.		

In contrast, a typical Schumpeter Mark II sector is relatively closed to new or small innovators and works in favour of large innovators. Therefore, we expect to observe a decreasing trend in the contribution of new firms. The number of firms may be relatively stable (as shown in table 1) or even decrease over time, depending on the size of exiting firms. This implies a rise in concentration of innovative activities in the sector which leads to relative stability particularly among big innovators.

To explore the dynamics of Schumpeterian patterns of innovation in the upstream petroleum industry, we need to measure the changes over time of these four variables. Comparing the observed trends with table 1 reveals the dominant pattern. We stick to the three main periods defined in the section 3. In order to smooth the trends and ignore the short term fluctuations, our measures are drawn from data collapsed within 4 years of the beginning and the end of the main periods, as shown in the figure 3. The length of the first period is 14 years, but the length of both the second and third periods are 10 years. Therefore, p1 is divided into one introductory sub-period (p1-0) and two other sub- periods (p1-1, p1-2). This means that all three main periods cover 10 years with two 4-year sub periods at both sides and a two year gap in the middle, leaving out the introductory sub-period of p1-0. Using this periodization helps to control for the impact of change in technological opportunities on the selected variables, and therefore unravels the role of knowledge base complexity in the dynamics of sectorial patterns of innovation.

Figure 3: Periodization of the Analysis



5.1. Concentration and number of innovators

The top part of figure 4 shows the trend of concentration of innovators over time for different size groups using a corrected version of Herfindahl index of concentration. This measure is used to explore the how the relative share of big vs. small innovators in the sector changes over time. The advantage of this corrected version is that it controls for small sample bias (Hall, 2000; Corrocher et al., 2007). We repeated the indicator for different subset of companies defined by innovation size (for N<40, N<100, N>40, N>100 and All companies: N is the number of patents each company holds) to check the robustness of the results in different size groups. The top left side of the figure (a) displays C for large innovation size group and top right side of the figure (b) shows it for smaller sizes. Regardless of the size categories, all of the indicators present an overall U shape pattern reaching their lowest points in p1-2 or p2-1. The two lowest figures show the number of innovative firms over time, by innovation size category.

According to these figures concentration (C) decreases in p1 (and even up to p2-1 for larger groups). In parallel, firm numbers (F) increase in almost all size categories. High technological opportunities driven by high oil prices seem to have worked as a powerful incentive for smaller firms to catch-up with major innovators. The increasing number of innovative companies in all groups also confirms the key role of new innovators in p1. Their considerable share in innovative activities challenged the relative position of big existing innovators pushing down the C index. Another complementary mechanism for the increasing number of firms and decreasing concentration could have been the progressive outsourcing strategy of oil operators to supply and service companies (Maleki, 2013).

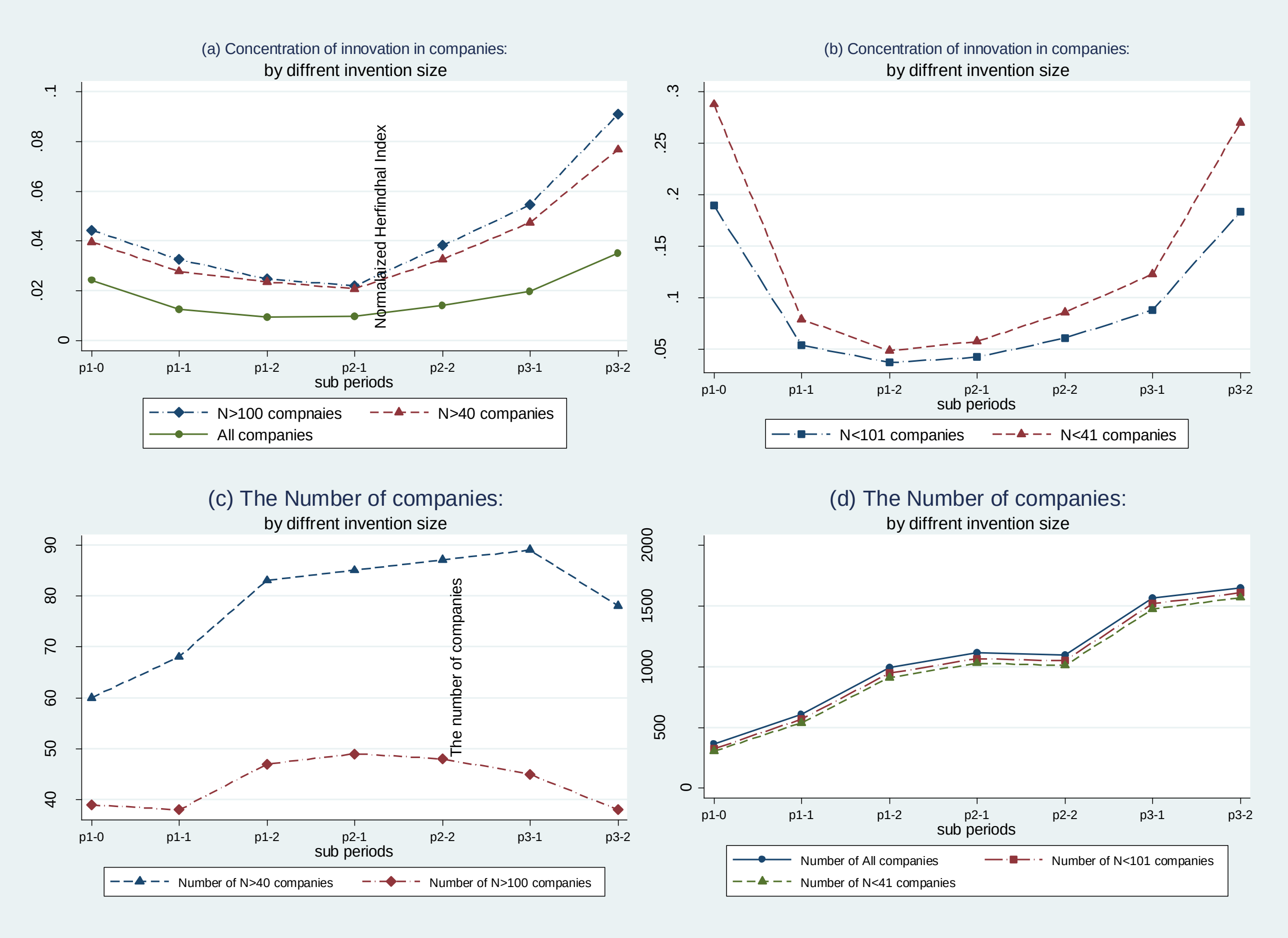
As oil prices collapsed in p2-1 and the declining trend continued in the second period, the upstream petroleum industry was not very rewarding for innovation. Over p2, F slightly decreased and C took a clear upward trend. One reasonable explanation could be the higher vulnerability of some smaller firms, when a continued low opportunity environment would dry up their innovative efforts. Due to the high risk and uncertainty involved in innovative activities, many firms may cut R&D investment in poor market conditions. As we know from previous section 3.1, the number of patents has a negative trend in p2. Yet increasing concentration of innovative activities, combined with reduction in the number of innovative firms, suggests vulnerability of smaller firms exiting from the sectorial system of innovation. Indeed, p2 is the only period with negative net entry. In addition, a wave of M&A activities, triggered by low oil prices in p2 was a complementary mechanism responsible for higher concentration.

The beginning of the third and final period (p3) presents an interesting and puzzling pattern. By the end of p2 and the beginning of p3 a new wave of innovative entry is observable resulting in a sharp rise of F (fig 4 d) in all size categories, with the exception of super big innovators (N>100) (fig 4 c). This should have been driven by the jump in technological opportunities observed after p2-1. Although F transforms sharply from a negative trend in p2 to a sharp positive trend in p3, there is not any corresponding drop in C. In contrast, C continues its upward trend which is reinforced over p3.

This pattern reflects the relative low and weakening share of new entrants in p3, compared to big incumbents (figs 4a & b). In addition, the short term jump of F before p3-1 (fig 4b) turned into a relatively stable trend in p3, whilst concentration gained momentum.

These patterns suggest a fundamental difference between p1 and p3. We observe that high opportunity environments in both periods encourage new innovators to enter into the sector - reflected in the rise of F. However C presents opposite trends - decreasing during p1, but increasing during p3. The key question is: how do we explain the fact that during p1 new small innovators could benefit from high opportunity conditions and challenge the position of bigger established firms, whilst during p3, established big innovators gain much more than new innovators from the expansion of the search space?

Figure 4 Concentration of innovative activities (a & b) and the number of innovative firms (c & d): by innovation size



The answer lies in the changing nature of technological regimes, as our evidence on the rise of knowledge base complexity in section 3 suggests. We observe that increasing systemic complexity of the knowledge in p3 is associated with higher concentration of innovative activities of the sector. A similar argument was proposed by Breschi et al. (2000) regarding the other elements of technological regimes such as appropriability and cumulativeness, although complexity is a relatively neglected element. Ceteris paribus, they argue that high technological opportunities favour a reduction in concentration, because they allow for entry of new innovators. The opposite relationship also holds for low opportunity conditions. On the contrary, according to authors such as Nelson and Winter (1982), Jovanovic and Lach, (1988),Winter, 1984; Dosi et al. (1995), conditions of high technological appropriability and cumulativeness could also lead to a rise of concentration. On the one hand, high appropriability limits the extent of knowledge spillovers creating relative advantage for big successful innovators. On the other hand, cumulativeness and concentration show a positive correlation, since the ability of existing big innovators to introduce new innovations is higher.

A similar dichotomy holds for systemic complexity where the difference between p1 and p3 can be explained by their underlying technological regimes. While in p1, small innovators could benefit from high opportunities because of low systemic complexity; this is not the case in p3. Systemic complexity in p3 would increase the cognitive barriers to entry for small and newcomer companies. Although there are high technological opportunities driven by recombination processes (as shown in section 3), they are mostly available to knowledgeable technologically diversified companies. They have access to the required knowledge segments as well as integrative and combinational capabilities. Small and new firms may innovate in specialized niche technical areas, but their relative role is lower. Under these conditions big incumbents have an advantage over small and new comers, because they benefit from their investment in innovation processes without major concerns regarding the risks of free riding and large externalities (Breschi et al., 2000).

5.2. Share of new entry to the system of innovation

This section analyzes the relative chance of new innovators in comparison with incumbents to contribute to the development of the knowledge base of the industry. Table 2 shows the number of patents of existing and new firms in each sub-period; and also the new innovators' share of patents (NE) in each sub-period. This is measured for the different innovation size (expressed as number of patents) of firms (with the minimum patent size of 1, 5 and 10), in order to get insights about the role of size for successful entry. The trend of NE is also shown in figure 5 for visual presentation.

Table 2: New entries to the innovation system: by different innovation size

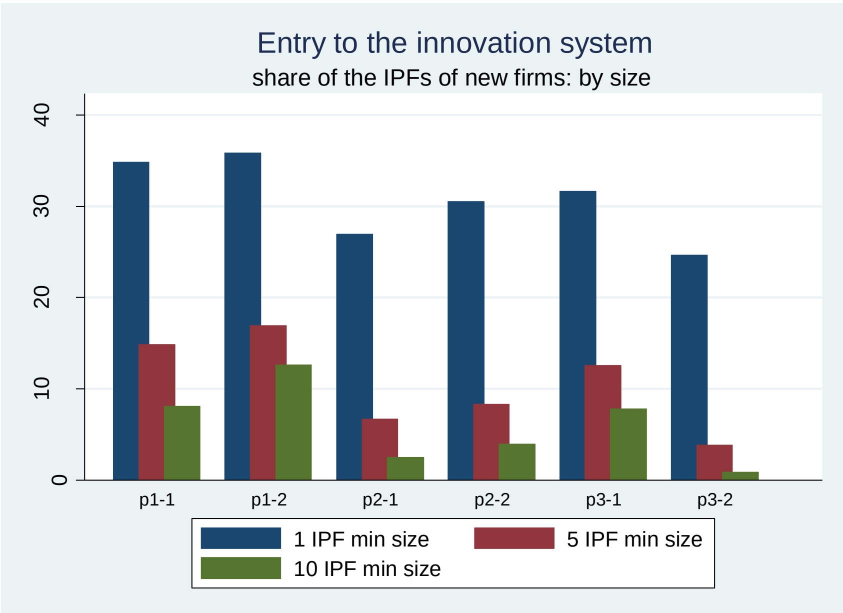
(a) New firms' share of patents: by size

	1 IPFs min size			5 IPFs min size			10 IPFs min size		
Sub periods	IFPs Existing Innovators	IPFs New Innovators	Share of new entry (NEP1)	IFPs Existing Innovators	IPFs New Innovators	Share of new entry (NEP5)	IFPs Existing Innovators	IPFs New Innovators	Share of new entry (NEP10)
p1-1	1297	693	34.82	1272	222	14.86	1222	108	8.12
p1-2	2205	1232	35.85	2166	442	16.95	2062	298	12.63
p2-1	2802	1033	26.94	2714	195	6.70	2588	67	2.52
p2-2	2528	1112	30.55	2459	223	8.31	2348	97	3.97
p3-1	4226	1957	31.65	4127	595	12.60	3952	337	7.86
p3-2	5291	1732	24.66	5089	203	3.84	4853	45	0.92

According to table 2, the share of new entry during period 1 (p1) increases from about 34.8 percent to 35.9 (NEP 1) confirming a 1% rise in the chance of new innovators. This is considered significant, because the indicator is drawn from the whole population. A test of significance would not be relevant, because no sampling method is applied. Growth of new entries seems higher for bigger innovators (about 2% and 4% for 5 and 10 IPFs minimum size), suggesting the increasing possibility of moving up of the hierarchy among larger firms. Overall, the new entry indicators confirm the increasing chance of new innovators over p1 for all firm sizes.

Transition from p1 to p2 is accompanied by about a 10% reduction of new entry for all size ranges. It is rather intuitive that the arrival of low opportunity conditions in p2 has worked against new entries, as the expected returns on R&D has reduced. Over p2, when low innovation opportunity conditions are established and companies have adjusted to the external shock, part of this lost contribution of new entrants recovered. This is reflected in the rise of NE for all size innovators (see table 2). This is rather counter intuitive, because low opportunity conditions do not motivate new innovative entries.

Figure 5 The percentage share of the IPFs by new innovators



According to the historical records (Weston and Johnson, 1999), one reasonable explanation is that new innovative companies emerged as a result of accelerated outsourcing of operators whereby part of innovation process transferred to a new class of agents i.e. service companies. In fact in many cases, operators supported the formation of specialized service companies as a result of poor market conditions. A horizontal disintegration strategy was followed to reduce fixed costs and increase specialization, efficiency and responsiveness. This rather long term response of oil operators to the unsuitable economic environment created a new division of labour in which part of the locus of innovation in the upstream petroleum industry transferred to new entities. As a result, our evidence tends to attribute the rise of new entries over p2 to the emergence of a new division of innovative labour in the industry reflecting also a new division of knowledge among industry participants.

The distinction between short term and long term responses of the sectorial innovation system to low opportunity conditions is an interesting finding. According to this theory, short term response of industry to low opportunities was a reduction of new entries. However, the long term response was formation of a new division of knowledge or more precisely new industry architecture (Brusoni and Jacobides, et al., 2009). This favoured new entrants and launched a new knowledge dynamic. Transition from the low opportunity conditions of p2 to high opportunity conditions in p3 amplified these new entrants as reflected in the continued rise of NE for all sizes ranges from p2 to p3.

Over p3, we observe a relative reduction of new entrants in all groups, to their lowest levels over the whole period of observation. In contrast to the high opportunity conditions of p1 over which new entries experienced their maximum level, the possibility of new entries over p3 seems to reach to its most limited status. Ceteris paribus, the standard theory of patterns of innovation predicts a positive relationship between opportunities and new entries . These predictions however are conditional on the nature of technological regimes. For example, high new entry is expected under low cumulativeness conditions when “would-be innovators are not at major disadvantage with respect to incumbent firms” (Breschi, et al., 2000, p.393). Our analysis in section 3 suggests that the difference between p1 and p3 in terms of new entries can be attributed to the dynamics of knowledge base complexity. New entrants are at a high disadvantage in p3 compared to p1 because of the change in underlying technological regimes. The rise of systemic complexity over p3 involves higher cumulativeness, implying higher cognitive barriers to entry. This constrains the exploitation of high technological opportunities by new and small companies in this period.

6. Sectorial patterns of innovation and knowledge base complexity

So far, the dynamics of the sectorial pattern of innovation in the upstream petroleum industry are analyzed with respect to three indicators over the main periods. Table 3 summarizes the changing pattern of these indicators where each period is labelled with the dominant pattern.

Arrows specify the magnitude of changes in the indicators over that period, according to the data presented in previous sections (see table 2). Accordingly, p1 are characterised as strong Mark I, because of a considerable reduction in the concentration, a large increase in the number of firms and the rise of new entrants.

Table 3 Dynamics of Schumpeterian patterns of innovation

Periods	1st period	2nd period	3rd period
Schumpeterian pattern of innovation	Strong I	Weak II	Strong II
Concentration (C)	↓↓	↑	↑↑
Number of firms (F)	↑↑	↓	-
Entry of new firms (NE)	↑	↑	↓

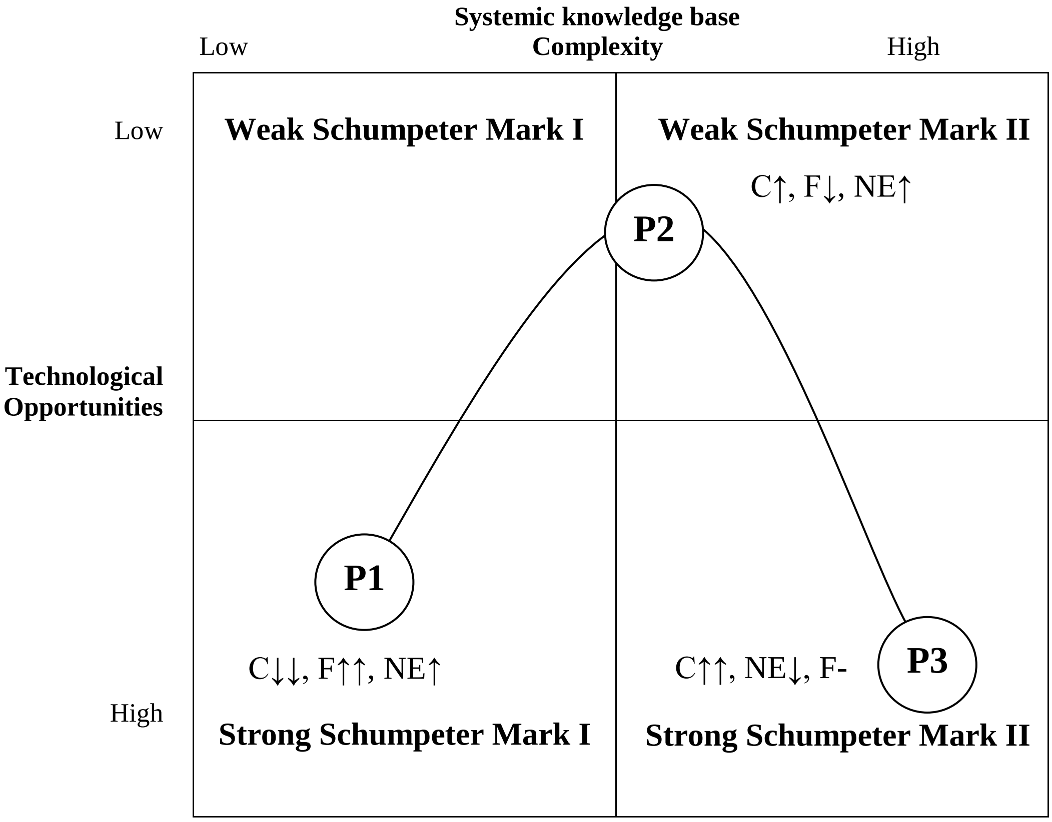
The second period presents a pattern which is more similar to Mark II, although its signals are still weak. Concentration (C) began a slight upward trend and F reduced to some extent, as technological opportunities were relatively low. Although NE shows an upward trend over p2, this can be explained by the accelerated outsourcing of oil operators driven by low oil prices (Weston and Johnson, 1999). In the absence of this structural change, we could have observed higher concentration, less number of innovative firms, and downward new entries. Hence, this period could be labelled as Mark II, putting aside the effect of structural change on new entries. The combinations of these results with those relating to the dynamics of knowledge base complexity in section 3 suggest that this factor contributes to explain change in innovation pattern during p2. Systemic complexity favours big incumbents and works against small and newcomer firms. This is reflected, although less strongly compared to p3, in the trend of the indicators in p2 which fits with Schumpeter Mark II.

The signs of Schumpeter Mark II get considerable strength when technological opportunities increase over p3 (as the patterns of indicators show in table 3). Although technological opportunities are high, new entries are reduced and the number of firms stays relatively stable. Most importantly, the upward trend of concentration accelerates. When the three indicators are combined, comparing table 1 and table 3 signals the emergence of a progressively stronger Mark II . The high barriers of entry in this period for new small companies and relative advantage of big incumbents is attributable to the systemic complexity of the knowledge base. The rise of technological complexity of the sector was driven by more sophisticated upstream exploration and production projects where the available standard technologies did not simply work. As a result a few big technologically advanced companies had access to the sophisticated technology and could operate these complex projects. In conclusion, the upstream petroleum industry presents an interesting dynamic, beginning with a strong Mark I over p1 which gradually weakens and transforms to a weak Mark II over p2. This weak mark II style is reinforced over time, ended up in a pattern resembling a very strong Mark II.

Our results also suggest that change in technological opportunities tends to associate with the pace of change in existing patterns of innovation. The existing pattern of innovation is weakened when changing from high to low opportunity (as observed over transition from p1 to p2) and is reinforced when changing from low to high (as observed over transition from p2 to p3). However, this evidence on its own is unable to explain the shift from Mark I to Mark II. This is best understood by looking at the two extremes of p1 and p3, when two different patterns of innovation are observable while technological opportunities are high. If the concept of technological regimes is to convincingly explain the shifts in the mode of Schumpeterian pattern, other factors should be taken into account. Our results signal that systemic knowledge base complexity (see section 3) is a reasonable candidate in the case of the upstream petroleum industry, In that a reduction of systemic complexity over p1 is consistent with Schumpeter Mark I. When systemic complexity of the knowledge base increases in early p2, the features of Mark II emerge in the sector. Then, higher opportunities in p3 reinforce this pattern.

These findings clearly support the hypothesis of this article. As predicted, the upstream sector seems to move toward Mark I over p1 and shift towards Mark II over p3. This leads us to posit a novel analytical framework which explains the dynamics of sectorial patterns of innovation according to technological opportunities and, in particular, knowledge base complexity in upstream petroleum. The impact of the combination of these two dimensions of technological regimes on change of pace and mode of Schumpeterian pattern of innovation is visualized in a 2x2 matrix in figure 6. The vertical axis specifies the high vs. low technological opportunities and horizontal axis represents the pace of systemic complexity. As argued in section 3, the dynamics of systemic complexity could favour the dominance of two different types of Schumpeterian pattern of innovation (Mark I on the left and Mark II on the right of the matrix differentiate these two types). Increasing (decreasing) technological opportunities tends to reinforce (weaken) the pace of existing pattern, whether it is Mark I or II, but do not alter its mode.

Figure 6 Technological regimes and Schumpeterian pattern of innovation



The curve in figure 6 shows how the upstream petroleum industry has travelled through different sectorial patterns of innovation during different periods. The circles represent the main three periods of p1, p2 and p3 beside which the trend of indicators is shown (according to the table 3). The location of each circle in the matrix represents the configuration of two elements of technological regimes shaping sectorial pattern of innovation. In summary, our framework is able to describe how/why an industry that initially emerged as a strong Mark I, later developed into a weak Mark II and finally became a strong Mark II.

7. Conclusion

This study was an intellectual attempt to explain how the changing sectorial patterns of innovation nature are associated with dynamics of technological regimes. We investigated the dynamics of sectorial patterns of innovation within a Schumpeterian framework and its link to changing nature of sectorial technological regime.

The hypothesis developed based on this analytical framework address the co-evolution among knowledge base complexity, technological opportunities and sectorial patterns of innovation. Our evidence suggests that decreasing systemic complexity is more associated with Schumpeter Mark I, while the rise of systemic complexity implies a shift towards Schumpeter mark II.

This study offers three contributions in order to examine the suggested hypothesis. First, a methodology has been suggested in order to capture the dynamics and evolution of mode of sectorial patterns of innovation. The second contribution is the application of a suggested methodology in the upstream petroleum industry which illustrated novel empirical observations in the dynamics of sectorial knowledge base. Thirdly, this theoretical framework posits that change in the nature of knowledge environment implies structural change in the industry.

The hypothesis of this study (see section 4) is supported by our results. A shift of Schumpeterian patterns of innovation from Mark I to Mark II after early in p2 (around 1987) is followed by a more pronounced correlation between systemic complexity and emergence of Mark II in p3 (about 1995). We also argue that the dynamics of technological opportunities (i.e. C; F; and NE) are not sufficient to explain this shift of mode, although they can explain changes in the pace or strength of existing Schumpeterian patterns. When the dynamics of technological opportunities are analyzed in combination with knowledge base complexity as two different dimensions of technological regimes, they convincingly explain the dynamics of Schumpeterian patterns both in terms of pace and mode. In other words, change in systemic knowledge base complexity could alter the Schumpeterian mode, while a rise (decline) of technological opportunities tends to weaken (strengthen) the existing mode without altering it. Both small and new innovators could exploit increasing technological opportunities most when systemic complexity is low or decreasing. This resembles most, the features of Schumpeter Mark I mode. In contrast, when systemic complexity becomes dominant in the sector, the rise of technological opportunities is relatively more beneficial to large and incumbent companies. This situation characterizes the Schumpeter Mark II mode.

Hence, while the nature of knowledge components underlying the sector may have not changed considerably, the intensity of interactions between knowledge components increased, leading to higher systemic complexity and knowledge cumulativeness of the sector in recent periods. This situation reinforced the relative position of incumbents compared to new firms and increased the barriers to entry. Put it differently, technical change was more of a ‘competence-enhancing’ type (Tushman and Anderson, 1986) where incumbents have higher capacity to assimilate new but similar knowledge. High technological opportunities can reduce the gap between small and big innovators when systemic complexity is decreasing (Mark I). However, high technological opportunities are most likely to widen the gap between small and big innovators, if systemic complexity dominates the sector (Mark II).

In our analysis of the shift towards Mark II, sizeable innovators were not always incumbents, which make the sector structurally dynamic. As we documented elsewhere (Maleki, 2013), knowledge connectors or integrators have emerged as complementary players enabling incumbents to cope with excessive complexity. In addition the distinction between innovation size and firm size is important to be taken into account, as sizable innovators are not necessarily biggest players in the sector. This issue however is the focus of a separate forthcoming paper which will modify the established view on Schumpeter Mark II.

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