

**THE EFFECT OF THE DYNAMICS OF KNOWLEDGE BASE COMPLEXITY ON SCHUMPETERIAN  
PATTERNS OF INNOVATION: THE UPSTREAM PETROLEUM INDUSTRY**

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## 1. Introduction

This paper addresses important changes in innovation patterns in the upstream petroleum industry over the period from the 1970s to 2005. It argues that the shifts in patterns of innovation over that period can be explained by the dynamics of knowledge base complexity (KBC). A knowledge base is defined as complex if it involves integration and combination of different scientific and technological disciplines and requires a variety of competences (such as R&D, design, engineering and production). We develop a quantitative method to explore KBC and show that increasing KBC has shifted innovation patterns, from a broadly Schumpeter Mark I to a 'modified' form of Schumpeter Mark II, led less by the established oil majors, but by a new class of integrated service companies.

The petroleum industry has a relatively long and complicated value chain, beginning with exploration and production of crude oil, to transport, refining and retail. The upstream industry comprises a set of related activities related to: oil and gas exploration, together with heavy oil, condensates and tar sands; developing reserves for extraction, production over an extended lifetime; and finally decommissioning after depletion. It includes the business activities supporting and supplying these main activities, including for marine, sub-sea, and complex geo- activities.

While the notion of technological regimes has proved powerful in explaining inter-sectoral differences in sectoral patterns of innovation, the analysis of the relationship between technological regimes and patterns of innovation at different stages of development of a given industry remains rather unexplored (Krafft et al., 2014). Our research aims to show how the changing nature of the sectoral patterns of innovation is intrinsically related with the dynamics of technological regimes. We provide a threefold contribution. First, we propose a dynamic reading of the concept of technological regimes and analyse structural transformation within the upstream petroleum sector over time. Second, we conceptualize and put the notion of KBC at the centre of our analytical framework. Third, we propose a quantitative method using patent data in order to capture the dynamics of KBC and their relationship with Schumpeterian patterns of innovation. We empirically test these ideas in the upstream petroleum industry focusing on changes in technological opportunities and KBC.

The novelty of our study consists of its focus on the dynamic relationship between KBC and the evolution of sectoral patterns of innovation. Most other works on technological regimes are in a static cross-sectoral mode which ignores the important role of change in the nature of knowledge for industrial dynamics. However, the recent study by Krafft et al (2014) provides evidence regarding the relationship between change in knowledge base characteristics and industry structure in the pharmaceutical industry.

Our study shows three distinct periods of technological innovation in upstream petroleum. The first period, to the end of the 1970s, was characterised by a rising trend of investment seeking advanced technology to diversify supply sources in more challenging reservoirs in the wake of the first and second oil shocks. We show that this period is characterised by a rapid rise in patents which can be explained by upstream factors driven by high oil prices. We characterise this period as a Schumpeterian Mark I type dynamic characterised by *creative destruction* where new firms play a major role in innovative activities and barriers to entry are low.

The second period, from the mid-1980s to the mid-1990s, was characterised by oil price cuts. Low oil prices seemed to act as a disincentive for innovation in the industry. As a result, patenting in upstream petroleum industry stagnated. Major companies restructured whilst new smaller specialised supply and service companies expanded

due to the outsourcing strategies adopted by many operators. The period, we find, shows a gradual shift in innovation patterns away from Schumpeter Mark I type weakly towards what resembles Mark II - where large firms increasingly play a major role in technological activities and it becomes challenging for new small innovators to enter.

The third period has a more complex dynamic, but with major implications. The sharply upwards trend in innovation from 1994, was not driven by higher oil prices, which did not increase for a further six years. Our data suggest that the emerging pattern in this period in upstream petroleum industry is not a typical Schumpeter Mark II, but a modified version of it, because established oil operators did not have a strong influence on this concentrated innovation pattern. Instead, a new class of agents (integrated service companies) led the sector towards a 'modified' Schumpeter Mark II.

The paper is organised as follows. Section 2 presents a dynamic reading of the concept of technological regimes and explores the knowledge gaps in the literature. In section 3 we introduce our method, showing how we measure technological opportunities, KBC, and dynamics of sectoral patterns of innovation. Section 4 presents our results, focusing on dynamics of technological opportunities, knowledge base complexities and Schumpeterian patterns of innovation. We then discuss the relationship between Schumpeterian patterns of innovation and the dynamics of KBC. Section 5 summarises our findings and concludes.

## 2. Literature Survey

We review three related bodies of relevant literature: on the Schumpeterian patterns of innovation; dynamics of technological regimes; and on complexity.

### 2.1 Schumpeterian patterns

In the Schumpeterian tradition, the distinction between Mark I and II has proved a useful analytical tool to distinguish different sectoral patterns of innovation among different industrial sectors. In this article, we ask whether the Schumpeterian dichotomy is a useful analytical tool to understand *whether, how and why patterns of innovation differ in the same industry over time*. Our intuition is that the innovation patterns and knowledge accumulation in one industry may gradually change as a result of technical change and the associated division of labour. As an industry evolves, its knowledge base can move to higher orders of complexity which involves both higher differentiation and requires greater integration capacity, creating a shift in the Schumpeterian pattern.

Schumpeter Mark I is characterized by *creative destruction* where new firms play a major role in innovative activities and barriers to entry are low. In contrast, *creative accumulation* is the main characteristic of Schumpeter Mark II, and established firms play a major role in technological activities whilst it is challenging for new small innovators to enter (Schumpeter 1934, 1942). Authors such as Malerba and Orsenigo (1995, 1996, and 1997), Breschi et al. (2000) and Malerba (2007) found empirical support for the existence and significance of these patterns.

Notwithstanding those key findings, these studies suffer from two limitations. First, the methodology employed does not allow for the observation of variations *within* technological classes and industries, because the analysis relies on aggregated data. Second, it does not allow for the observation of *temporal variation* in sectoral patterns of innovation within industries, because the time dimension is removed. So while it is widely accepted that patterns of innovation change over time, observations are based on average behaviour over time for specific technology fields (Malerba and Orsenigo, 1996).

These limitations have been partly addressed in more recent studies. For example, Corrocher et al. (2007) observed the co-existence of both Schumpeterian patterns of innovation in the ICT industry. Grebel et al. (2007) provided similar evidence, stressing the co-existence of large diversified and new technology firms within innovation networks in knowledge intensive industries like biotechnology and telecommunications.

Addressing the second limitation, Malerba and Orsenigo (1996) explicitly acknowledged 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)’ (p. 97).

Malerba and Orsenigo (2000) and Malerba (2005) also argued that analysis of the knowledge base is a key requirement to develop an in-depth understanding of the innovative dynamics within sectors. Malerba (2006) 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’ (p. 14-15). 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.

## **2.2 Technological regimes in a dynamic perspective**

The notion of technological regimes was introduced by Nelson and Winter (1982), referring to the knowledge environment in which firms operate, or in which their problem-solving activities take place. More recently, four building blocks were identified: technological opportunity, the appropriability of innovations, their cumulativeness, and knowledge base properties (Breschi and Malerba, 2000; Breschi et al., 2000). We focus on the co-evolution between technological opportunities and knowledge base properties. *Technological opportunities* refer to the likelihood of innovation in a particular sector resulting from a given investment in search processes. Over the industry life cycle (ILC), technological opportunities may significantly change suggesting its dynamic nature. The standard ILC model assumes that opportunity conditions decrease when industries 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; Mendonça, 2009; Hirsch-Kreinsen, et al., 2006; Von Tunzelmann and Acha; 2005) show that this is not necessarily the case.

The properties of the knowledge base which shape innovative activities constitute a synthetic construct encompassing the degree of *specificity*, *tacitness*, *complexity* and *independence*. *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* refers to the extent to which knowledge that is relevant to innovative activities can be separated. Like other dimensions of technological regimes, these properties of the knowledge base can change over time as a result of new application, inter-industry knowledge flows, codification practices (Steinmueller, 2000), and new instrumentation and computational capabilities (Arora and Gambardella, 1994).

Changes in one or more of these dimensions of technological regime are likely to have important implications for sectoral patterns of innovation (Malerba and Orsenigo, 1995; 1996; 1997; Malerba, 2007). We test this intuition in the upstream petroleum industry with particular emphasis on the dynamics of KBC. 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, and production) for innovative activities. So far, the role of KBC has been comprehensively addressed only by a few studies, including Vale and Caldeira (2008) investigation of the footwear industry and Iizuka (2009) account of structural change in the Chilean salmon farming industry.

### **2.3 Complexity**

The concept of complexity has several distinctive types and definitions. A key 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. This specific notion of knowledge complexity matters 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). This kind of complexity contributes to shape industrial dynamics since 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).

Knowledge indivisibility is the outcome of a process whereby systemic knowledge serves new functions which are not achievable by individual bits of knowledge. In sectors with high levels of such complexity, successful innovation is not possible without a full understanding of the compatibilities and complementarities of diverse technologies. Because the source of this complexity is often *systemic innovation* (Chesbrough and Teece, 1996), we label this type of complexity as *systemic complexity*.

## **3. Method**

Our method rests on integrating three related approaches: patent analysis to measure the dynamics of technological opportunities; measures of KBC; and measures of sectoral patterns of innovation.

### **3.1 Measures of technological opportunities**

We analyse the transformations of sectoral innovation systems in upstream petroleum using the Derwent Innovating Index, the 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 International Patent Families (IPFs) which group similar inventions registered in different territories. This is to avoid multiple counting of the same invention registered in different countries. Patent counts are used as a proxy to capture of the dynamics of the innovative performance.

Patent data is the only rigorously classified information on 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, 1985; Griliches, 1990; OECD, 2009): (i) Not all inventions are legally patentable everywhere. The classic example is software which in many countries is protected by copyright. Moreover, the patenting scope may differ from one country to another depending on

their particular patent law; (ii) Because of different institutional structures in different countries which affect the length, time and effectiveness of protection, an inventor's incentive to file for patents vis-à-vis use other forms of protection varies substantially; and (iii) Propensity to patent varies across industries.

While patents are only imperfect measures of innovation order, our results are less affected because the conclusions in this study are based on the analysis of *trends* rather than absolute levels of the variables. Therefore, we do not expect imperfections to significantly impact on trend analysis.

Following previous studies, such as Andersen (2005); Park and Lee (2006) and Fai (2007), we use patenting growth rate to capture the dynamics of technological opportunities in upstream petroleum. We employ variation in patenting rate to examine how technological opportunities change over time. This analysis contributes to the understanding both of sources of variance in technological opportunities as well as its impact on industry performance as measured by R&D intensity and productivity (Klevorick et al., 1995).

### **3.2 Measurement of Knowledge Base Complexity**

Here we explore how the level of KBC changes over the ILC. We aim to understand how the level of KBC evolves over different periods and how major innovators cope with its dynamics.

According to the definition introduced in section 2.3, proxies to measure complexity should consider the links and interactions between different elements of the knowledge base and capture the recombinant nature of knowledge. In order to measure systemic complexity, network representation of the knowledge base is very relevant. According to this view (Saviotti, 2011; Krafft and Quatraro, 2011), the knowledge base has a co-relational structure comprised of nodes and links between these nodes. Nodes are technology classes and links represent relationships between technologies connecting nodes together. The measure of systemic complexity should consider 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.

Network analysis indicators treat 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 the 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 and Quatraro, 2011).

In social Network Analysis (SNA) 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 for which two technological classes appear joined together (Krafft and Quatraro, 2011). Among various measures available to describe the network connectivity and structure of the knowledge base, *network density* is one of the most used. It considers the total number of links in a system as a proportion of the total number of possible 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 and Quatraro, 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, 2011).

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

$$DC_n = \sum_{i \in N, i \neq n} l_{ni} \quad (1)$$

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

The *degree of centrality* 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 and Quatraro, 2011), as shown in the following equation:

$$NDC_n = DC_n / (N - 1) \quad (2)$$

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. *Degree of centrality* characterises a single node, not the network. To create a measure of connectivity at the level of a network, we rely on the *average* of the degree of centrality of all nodes of the network. Following (Krafft and Quatraro, 2011), we used the *average* measure of *degree of 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:

$$WADC = \sum_n [NDC_n * (P_n / \sum_n P_n)] \quad (3)$$

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

### 3.3 Measurement of sectoral patterns of innovation

The indicators selected for the analysis of the dynamics of sectoral patterns of innovation are based on previous studies (Malerba and Orsenigo, 1996; 1997; Breschi and Malerba 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.

Although the variables of this inter-temporal research are similar to previous cross-sectoral studies, their operational correspondence with archetypical Schumpeterian patterns of innovation is interpreted differently. Due to the dynamic nature of the analysis, we are more interested in the variables' trends than in their values in cross-sectional designs. In other words, our interpretation is based on relative change (of the variables) over time, indicating whether at different points in time upstream petroleum was moving closer to a typical Mark I or Mark II type.



## 4. Results

Our results are compiled in five sub-sections: our periodization of trends of technological opportunities; the dynamics of KBC over those periods; the consequences of that complexity; the dynamics of Schumpeterian patterns of innovation; and the resulting changes in sectoral patterns of innovation.

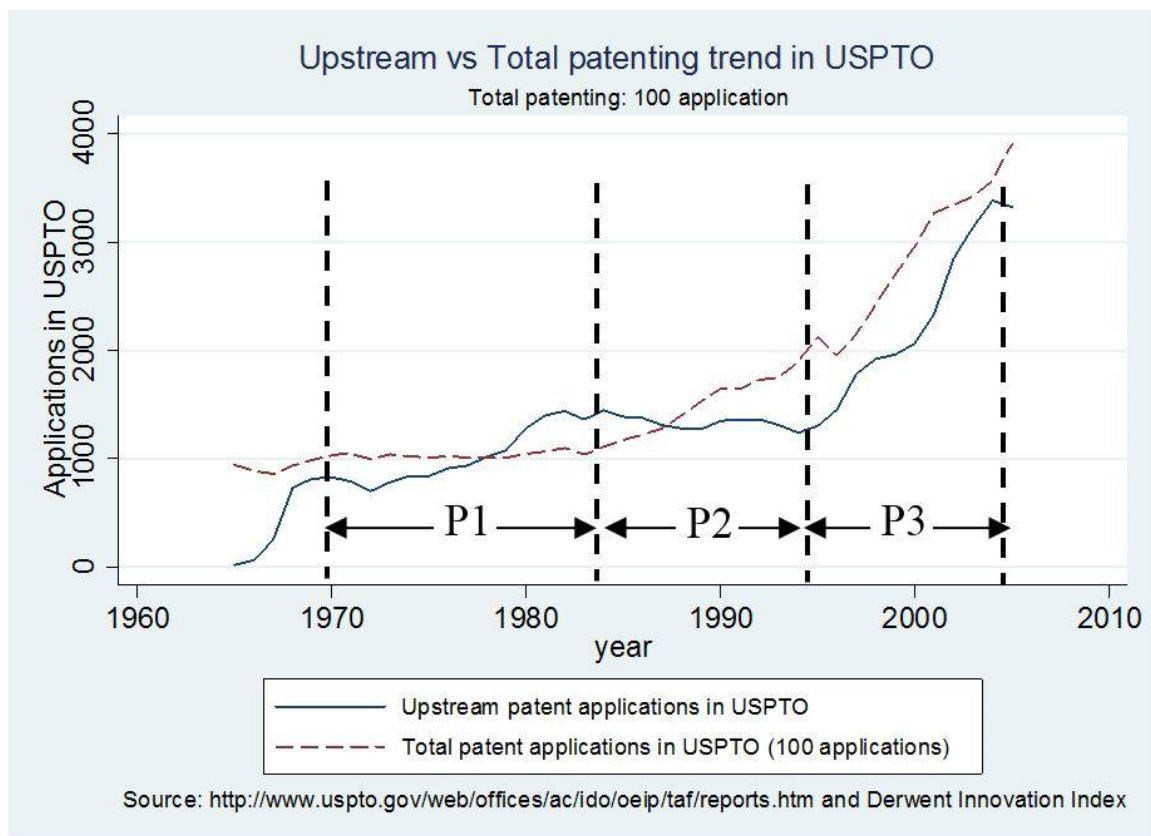
### 4.1 The trend of technological opportunities

Following previous studies, such as Andersen (2005); Park and Lee (2006) and Fai (2007), we use patenting growth rate to capture the dynamics of technological opportunities in upstream petroleum. We employ variation in patenting rate to examine how technological opportunities change over time.

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 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 upstream petroleum presents three distinct periods over the last four decades. From the early 1970s until 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). The third period begins after 1994 when the industry grows and looks very innovative (p3).

Figure 1: the number of US patent applications over time



The first period corresponds to the first and second oil shocks driven by a wave of petroleum nationalization in Arab countries, Iranian revolution and increasing oil consumption which pushed up oil prices. These events provided powerful motives for upstream R&D investment seeking advanced technology in order to diversify supply sources. The aim was to open up more 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 increase reserve replacement ratios (Fagan, 1997). The stable trend of total patenting (dash line) in this period also suggests that the rise of innovation is not attributable to this overall global innovation trend and should be explained according to upstream industry-specific factors.

Technological progress consequently led to excessive supply, pushing down oil prices for more than one and a half decades. Patenting took a negative trend from the mid-1980s to the mid-1990s. The second period shows about a 15% decline in upstream innovation while total global patent applications move in the opposite direction expressing a growth of more than 70% over the period. This suggests that low oil prices acted as a disincentive for innovation.

The collapse of oil prices in mid 1980s was a major driver for industry restructuring and emergence of new industry architecture. As a result of sustained low oil prices, oil majors implemented cost reduction programs to increase their efficiency. Fluctuations around the average low prices drove them to change their cost structure from fixed to variable. They chose to lease many types of equipment from previously owned service companies. The aim was to increase flexibility and responsiveness to change (Weston and Johnson, 1999). This created a massive opportunity for supply and service companies to takeover some activities previously conducted by operators. Technological progress in the industry and the need for specialization was another key driver.

The 1986 counter shock was a key turning point for oil service companies, pushing them towards horizontal and vertical integration strategies (Babusiaux et al., 2004). Similar to established operators, faced with a declining market in the second half of the 1980s, service companies also restructured themselves in order to increase efficiency. They redefined their portfolios, focusing on what they considered their main expertise, selling less relevant units. An external growth strategy was also undertaken by smaller specialized service companies in drilling and geophysical services (Barreau, 2002). The result was the relative expansion of specialized supply and service companies in the sector.

The third period is more complicated to analyse. While there was no major oil price changes until 2002, nor any technology-push trend (see the dash line in the figure 1) compared to the second period, the innovation performance of the industry increased dramatically. The number of patent applications in upstream petroleum grew about 170%, meaning that the period saw an explosion of the search space for new technologies in spite of the fact that oil prices remained low.

The innovation trend in upstream petroleum took a sharp upward trend after 1994, while oil prices begun to increase roughly 6 years later. Technology push contributed to explain this radical shift but it is not sufficient to explain the radical shift in innovative performance, that is from negative 15% growth rate in the second period to positive 170% growth over the third period (see figure 1).

We suggest that a combination of demand side factors (for innovative solutions) and change in industry architecture contributed to this dramatic change. Firstly, the cost of finding and lifting oil began to rise after 1995 (U.S. EIA, 2011), signalling that oil extraction was becoming an increasingly challenging business. Also, the provision of

equipment, design services and engineering services in upstream projects must adapt to the geological location and geophysical characteristics of the reservoir such as the shape, size, temperature, and type of rocks. Over time, easy to access reservoirs became depleted and companies had to deal with more difficult, less-accessible locations and more challenging conditions for extraction. Advanced and complex technology became a matter of survival, not just a tool for higher profits (U.S. EIA, 2011).

However, the industry architecture was mostly formed by operators and specialized service companies, which meant that it was not optimally structured to cope with the new technological imperatives of the sector (Chafcouloff et al., 1995). Given low oil prices and limited resources for innovation, a more efficient industry architecture was required to increase productivity and more quickly generate new technologies. Some major supply and service companies (such as Schlumberger, Halliburton, Baker Hughes, Weatherford) gradually began to provide a broad range of services to meet their client's expanding needs for bigger and more complex exploration and development projects. This trend had already begun towards the end of second period. The 'integrated solution' gained momentum as customer-relationship strategies when operators requested more packaged services instead of task-specific activities (Barreau, 2002). This increasing demand for integrated services pushed big supply and service companies to build project management and integration capabilities, previously the territory of major oil operators.

This third stage of evolution stemmed from the second phase, triggered by a search for a fuller degree of integration and exploitation of interactions and synergies between different activities. Near the turn of the century from 1998 to 2001, service and supply industry experienced mega mergers in which very big companies expanded their size while at the same time refocusing their activities. Such changes under continuous low oil prices had some distinguishing features. First, the scale of acquired assets was much larger. Second, the scope of integration encompassed several service segments for major service companies. The overall result was an unprecedented record of industry consolidation, similar to major oil operator consolidation in the same period (Barreau, 2002).

Larger scale M&A activities moved the sector to a more concentrated industry structure which can be interpreted as an organizational industry-wide response to the new technological imperatives (Teece and Armour 1976). Industrial restructuring spurred a wave of innovative solutions. Overall, the service intensity of E&P activities and their knowledge content significantly increased over time, which led Rajan (2011) 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.'(p. 11)

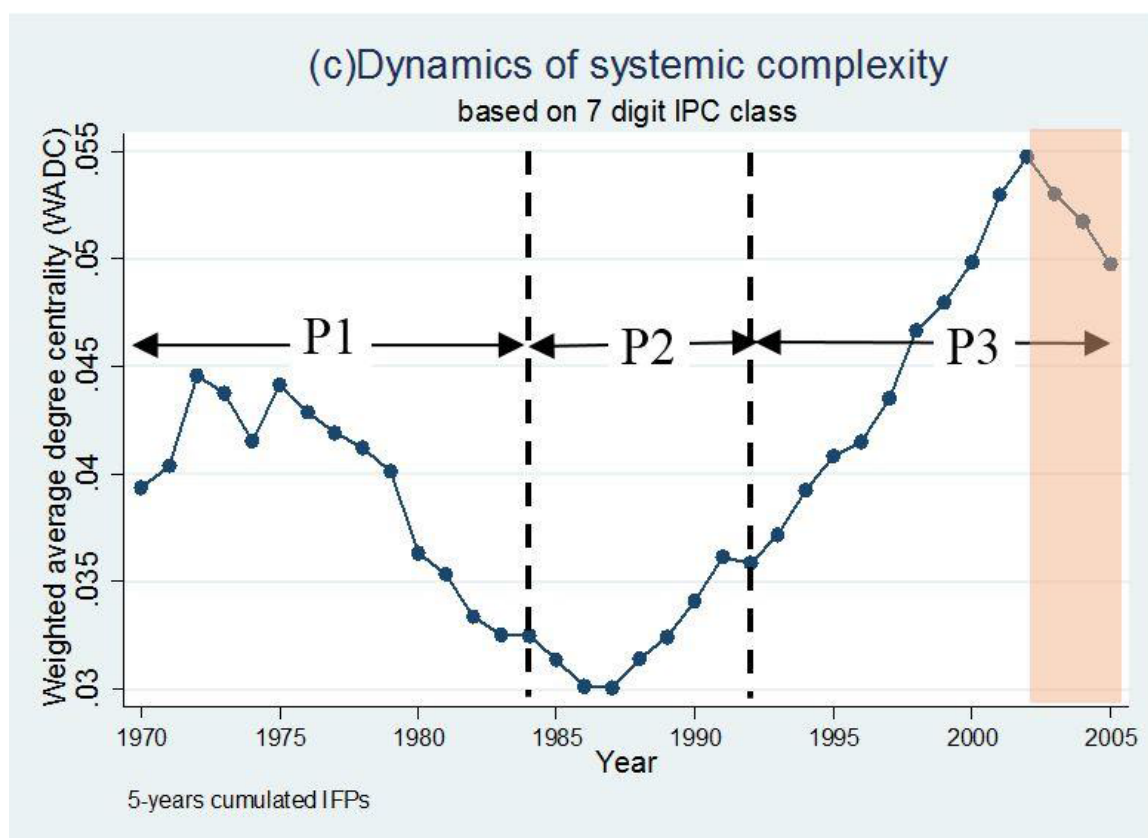
In sum, changes in industry architecture express three different phases after 1970 in parallel with innovation trends. The first phase is the period of oil shocks when operators have a dominant role and actively invest in technology. The second phase is the period of collapse of oil prices when limitation of R&D investments pushed down innovative activities. This triggered M&A activities among majors and service companies, and at the same time accelerated outsourcing strategies. The result was the relative expansion of specialized supply and service companies. The third phase saw the gradual emergence of new large service companies and a sharp increase in innovative activities is observable.

#### 4.2 The dynamics of knowledge base complexity

The dynamics of KBC in the upstream petroleum industry are presented in figure 2 using the WADC measure.

The trend of systemic complexity over most of the first period (p1) is downward, which indicates decreasing connectivity within the knowledge network. This process is driven by a higher rate of creation of new nodes (or new technological classes), compared to new links between new and existing nodes (Saviotti, 2011). 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 knowledge cumulativeness are relatively low.

Figure 2: Dynamics of the three dimensions of KBC in the upstream petroleum industry



Some data are missing in the post-2002 period (faded)

Historically, this was the period of rapid technological progress, when existing technologies (like 3-D seismic and horizontal drilling) were first introduced. When new promising technological fields are explored, it takes time for 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 regarding the trajectory and potential of the new technologies. The emergence of new technologies may be expected to create new but poorly connected nodes, and temporarily reduce the systemic connectivity of the

knowledge network (Saviotti, 2011). The first period in upstream petroleum reflects this proposition.

The situation began to change when the direction of systemic complexity reversed in the beginning of the second period (p2) in 1986, as connectivity within the knowledge network increased. This trend continued almost up to the end of p3. The diffusion and establishment of new technological fields explored in p1 contributes to explain the changing overall pattern in p3, 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 had become known to the industry's incumbents. Historically, this is when integrated service companies began to emerge. As it was difficult for established operators to manage the increasing range of specialized sub-contractors in different technical domains and coordinate the technological interfaces, integrated service companies took this role. They introduced total and integrated solutions combining different related technologies in unified packages (Barreau, 2002; Chafcouloff et al., 1995). Following Krafft and Quatraro (2011) and Krafft et al. (2014), we argue that search strategies gradually became *organized* rather than being *random*. *Explorative* behaviour was gradually replaced by *exploitative* strategies applied in the most productive technological areas. Innovation increasingly happened *within* technological classes which proved promising and fruitful, with a lower dispersion of R&D investment across fields. As a result of emergent complementarities, the knowledge base of the sector is not easily divisible or decomposable. The rise of knowledge network connectivity over most of p2 reflects these dynamics.

The post 2002 decline in WADC seems odd, but still compatible with our theoretical argument. It resembles a period of technological discontinuity whereby the speed of new links in knowledge networks fall behind new nodes, so knowledge connectivity declines. We suggest such change a trend is a consequence of the fact that information about knowledge links is delayed (in the data set) compared to information about the nodes. In other words, systemic innovations which result from combinations (links) of previous innovations (nodes) appear later.

#### **4.3 The Consequences of Knowledge Base Complexity**

During the early phases (p1 and early p2) of the ILC, the complementarities between new and old knowledge domains were not fully explored and knowledge linkages were not fully operational. Access to a wide range of complementary knowledge was not necessary for the innovation process. Therefore, we expect to observe an increasing role for new entrants relative to the role of big and established companies (or otherwise knowledge integrators) in the organization of innovation processes, and the sector to behave as a Schumpeter Mark I pattern.

When systemic complexity increased in periods 2 and 3, the sector moved towards a more organized search period and exploitative strategies became more pervasive (Krafft et al., 2011). Core technological domains were realized, technological trajectories were relatively clear and most productive complementarities and technical interdependencies were explored by industry participants. Innovative companies which connect and integrate different bits of knowledge were able to benefit from economies of scale and scope in both knowledge generation and exploitation 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.

High systemic complexity presents strategic advantages for technologically diversified actors that occupy central positions in the knowledge networks, compared to marginal players (Antonelli, 2003). As a result, more knowledgeable incumbents *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 tend to be higher and growth opportunities for small ones are limited. As a result, we expect that the sector will move towards a Schumpeter Mark II pattern. These propositions are examined next.

#### 4.4 Dynamics of Schumpeterian patterns of innovation in upstream petroleum

In this section, we analyse the sectoral pattern of innovation. Following the extant literature (Malerba and Orsenigo, 1996; 1997; Breschi et al., 2000), we use a set of variables to examine how the sector evolved over the three periods (see section 3.3). Unlike in previous research, these variables are employed in an inter-temporal mode of analysis to explore the shift of a sector's (upstream petroleum) patterns of innovation over time. Our analysis relies on quantitative data. Due to the dynamic nature of the analysis, our analysis is based on relative change (of the variables) over time, indicating whether at different points in time upstream petroleum was moving closer to a typical Mark I or to a typical Mark II type.

Table 1: Expected Schumpeterian Patterns of Innovation in a Dynamic Perspective

| Schumpeterian patterns of innovation | Schumpeter Mark I<br>Widening | Schumpeter Mark II<br>Deepening |
|--------------------------------------|-------------------------------|---------------------------------|
| Concentration (C)                    | ↓                             | ↑                               |
| Number of firms (F)                  | ↑                             | ↓ -                             |
| Entry of new firms (NE)              | ↑                             | ↓                               |
| Stability of ranking (STR)           | L                             | H                               |

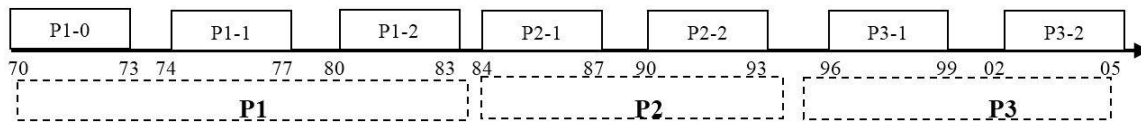
Table 1 summarizes the archetypical Schumpeterian patterns of innovation and the direction of the variables over time that we expect to observe in each typical mode (see 3.2.2). The Schumpeter Mark I sector is relatively open to the entrance of new or small firms. Therefore, we expect that new firm entry and the number of innovating firms will increase over time, and as a result the concentration of innovative activities will decrease. Malerba and Orsenigo (1997) term this process *widening*.

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 existing firms. This implies a rise in concentration of innovative activities in the sector which leads to relative stability particularly among big innovators. Malerba and Orsenigo (1997) term this *deepening*.

Comparing the observed trends with the evolution of technological opportunities (see table 1) helps to reveal the dominant pattern. We stick to the three main periods defined in section 3. In order to smooth the trends and ignore short term fluctuations, we collapse the data, as shown in figure 3. The length of the first period is 14 years, but the length of both the second and third periods is 10 years. Therefore, we divide p1 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 helps to unravel the role of KBC in the dynamics of sectoral patterns of innovation.

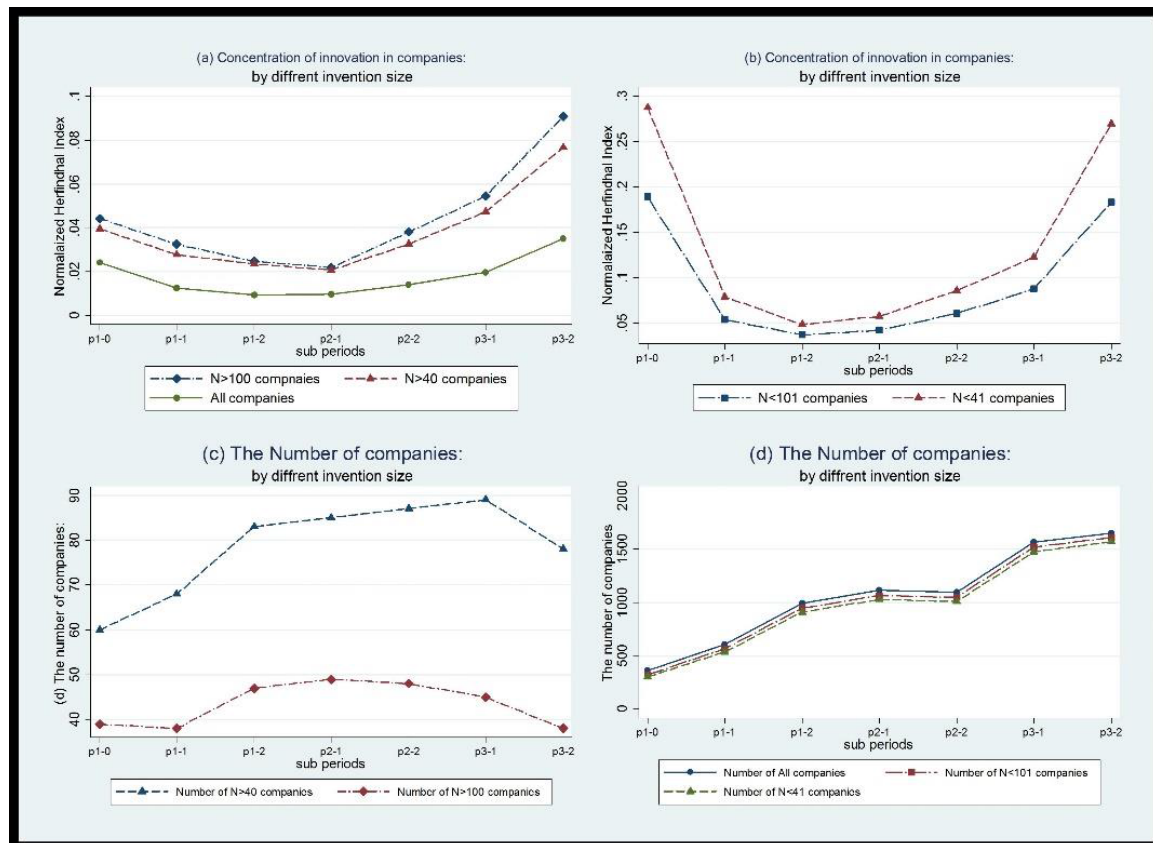
Figure 3: Periodization of the Analysis



#### 4.4.1 Concentration and number of innovators

The top part of figure 4 shows the trend of concentration over time for different size groups using a corrected version of Herfindahl index of concentration. This measure is used to explore how the relative share of big vs. small innovators in the sector changes over time.

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



The advantage of this corrected version is that it controls for small sample bias (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 4(a) displays concentration ( $C$ ) for large innovation size group and top right side of the figure 4(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.



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 concentration. Another complementary mechanism for the increasing number of firms and decreasing concentration was the progressive outsourcing of oil operators from 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 did not reward innovative efforts. Over p2, F slightly decreased and C took a clear upward trend. One reasonable explanation is the higher vulnerability of some smaller firms, when a continued low opportunity environment dries up their innovative efforts. Due to the high risk and uncertainty involved in innovative activities, many firms cut R&D investments in poor market conditions. As discussed in section 4.1, the number of patents has a negative trend in p2. Yet increasing concentration of innovative activities, combined with a reduction in the number of innovative firms, suggests vulnerability of smaller firms exiting from the system of innovation. Indeed, p2 is the only period with negative net entry. Furthermore, a wave of M&A activities, triggered by low oil prices in p2 provided a further contribution towards higher concentration. Nonetheless, acceleration of outsourcing strategies by oil operators smoothed the trend of concentration in p2, which otherwise would have been sharper.

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 4d) in all size categories, with the exception of super big innovators ( $N > 100$ ) (fig 4c). This was driven by the jump in technological opportunities observed after p2-1. Although F transforms from a negative trend in p2 to a sharp positive trend in p3, there is no expected 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. On the one hand, high opportunity environments in both periods encourage new innovators to enter the sector - reflected in the rise of F. On the other hand, C presents an opposite trend - decreasing in p1, but increasing in p3. These different behaviours are explained by the changing nature of technological regimes, in particular the rise of KBC discussed in section 4.2. In particular, we observe that the increasing systemic complexity of the knowledge base during p3 was associated with a higher concentration of innovative activities.

In sum, our results show that during p1, small innovators benefited from high opportunities because of low systemic complexity, which was no longer the case in p3. Systemic complexity in p3 increased the cognitive barriers to entry for small and newcomer companies. Although high technological opportunities emerged and were driven by knowledge recombination processes (see section 4.2), they could only be exploited by knowledgeable and technologically diversified companies, some of which possessed integrative and combinational capabilities. Small and new firms continued to innovate in specialized niche technical areas, but became less relevant in relative terms.



#### 4.4.2 Share of new entry to the system of innovation

This section analyses the ability 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 (by international patent family IPF) 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 three different innovation sizes of firms (with minimum patent size of 1, 5 and 10), in order to get insights about the role of size for successful entry.

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

| New firms' share of patents: by size |                          |                     |                          |                          |                     |                           |                          |                     |                            |
|--------------------------------------|--------------------------|---------------------|--------------------------|--------------------------|---------------------|---------------------------|--------------------------|---------------------|----------------------------|
| Sub periods                          | 1 IPFs min size          |                     |                          | 5 IPFs min size          |                     |                           | 10 IPFs min size         |                     |                            |
|                                      | IPFs Existing Innovators | IPFs New Innovators | Share of new entry (NEP) | IPFs Existing Innovators | IPFs New Innovators | Share of new entry (NEP5) | IPFs 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, confirming a 1% rise in the chance of new innovators. 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 the hierarchy among larger firms. Overall, the new entry indicators confirm the increasing chance for new innovators over p1 for all firm sizes.

The transition from p1 to p2 is accompanied by a 10% reduction of new entrants for all size ranges. The arrival of low opportunity conditions in p2 works against new entry, as expected returns on R&D are reduced. Over p2, when low innovation opportunity conditions were established and companies adjusted to the external shock, some of this loss of new entrants recovered. This is reflected in the rise of new entrants' share of all size innovators. This is rather counter intuitive, because low opportunity conditions do not normally motivate new entries.

One reasonable explanation, reinforced by data from Weston and Johnson (1999), 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 (service companies). Consequently, we 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 sectoral innovation system to low opportunity conditions is an interesting finding. The short-term response of industry to low opportunities was reduction of new entries. However, the long-term response was formation of a new division of knowledge, or more precisely a new *industry architecture* (Brusoni et al., 2009). This favoured new entrants and triggered new knowledge dynamics. Transition from the low opportunity conditions of p2 to high opportunity conditions in p3 amplified the number of entries, as reflected in the continued rise of NE for all size 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 1970-2005 period. In contrast to the high opportunity conditions of

p1 over which new entries experienced their maximum level, the possibility of new entries over p3 is most limited. *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 potential innovators are not at major disadvantage with respect to incumbent firms (Breschi and Malerba 2000). Our analysis in sections 4.2 and 4.3 suggests that the difference between p1 and p3 in terms of new entries can to a significant extent be attributed to the dynamics of KBC. 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, which constrained the exploitation of existing technological opportunities by new and small companies in this period.

#### 4.5 Sectoral patterns of innovation and KBC

So far, the dynamics of the sectoral pattern of innovation in the upstream petroleum industry has been analysed using three indicators over the main periods. Table 3 summarizes the changing pattern of these indicators with each period characterised by dominant pattern. The arrows in table 3 specify the magnitude of changes in the indicators over that period, according to the data presented in previous sections. Accordingly, p1 is characterised as strong Mark I, because of a considerable reduction in the degree of concentration (C), a large increase in the number of firms (F) and the rise of new entrants (NE).

The second period presents a pattern which is more similar to Mark II, although its intensity seems weak. 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 increased reliance of oil operators on outsourced services, a trend driven by low oil prices (Weston and Johnson, 1999). In the absence of this structural change, higher concentration and a lower number of innovative firms and new entries would probably have been observed. Hence, this period could be labelled as Mark II, except for the effect of structural change on new entries. Combined with the results presented in section 4.2, these results suggest that KBC contributes to explain change in innovation pattern as the industry entered p2, because increased connectivity within the knowledge network meant larger incumbents were in a better position to exploit technological independencies.

Table 3: Observed Schumpeterian patterns of innovation

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

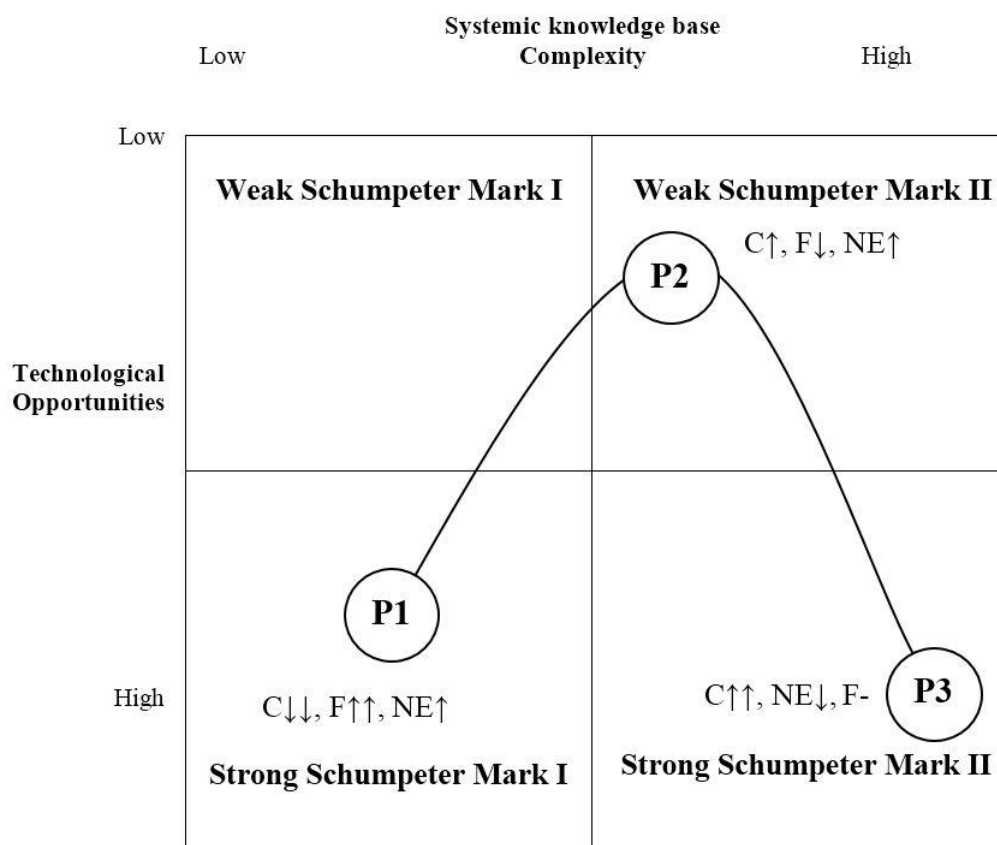
The signs of Schumpeter Mark II are considerably stronger when technological opportunities increase over p3 (as the patterns of indicators show in table 3). Although technological opportunities are high, new entries are reduced and the number of firms stays relatively stable. Most importantly, the upward trend of concentration accelerated. When the three indicators are combined, comparing table 1 and table 3 signals the emergence of a progressively stronger Mark II, in which the relative advantage of big operators coincides with higher KBC. The rise of technological complexity of the sector

was driven by more sophisticated upstream exploration and complex production projects. As a result, only a few big technologically advanced companies had access to the required range of sophisticated technologies and could operate these complex projects.

Our results also suggest that change in technological opportunities tends to affect 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 the transition from p1 to p2) and is reinforced when changing from low to high (as observed over the transition from p2 to p3). However, this evidence by itself 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 with high technological opportunities. If the concept of technological regimes is convincingly to explain the shifts in the *mode* of Schumpeterian pattern, other factors should be taken into account. We propose that systemic KBC is that candidate in the case of upstream petroleum. 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 fit well with the propositions outlined in section 4.3. 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 how the upstream petroleum industry evolved through different patterns of innovation in parallel with technological opportunities and KBC. The impact of the combination of these two dimensions of technological regimes on change of pace and mode of Schumpeterian pattern of innovation over the three periods is visualized in a 2x2 matrix in figure 5.

Figure 5: Technological regimes and Schumpeterian patterns of innovation



The vertical axis specifies high vs. low technological opportunities and the 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.

## 5. Conclusions

This paper aimed to show how the changing nature of sectoral patterns of innovation is intrinsically related with the dynamics of technological regimes. We provide a threefold contribution. First, we propose a dynamic reading of the concept of technological regimes to understand structural transformations of an industry over time. Second, we conceptualize and put the notion of KBC at the centre of our analytical framework. Third, we propose a quantitative method using patent data in order to capture the dynamics of KBC and their relationship with sectoral patterns of innovation.

Our focus is on the co-evolution among KBC, technological opportunities and sectoral patterns of innovation. Our evidence suggests that decreasing systemic complexity tends to be associated with Schumpeter Mark I, while the rise of systemic complexity implies a shift towards Mark II. Nonetheless, it is also evident from our findings that the Schumpeterian dichotomy is not completely adequate to capture the dynamics of complex sectoral innovation systems, as the third and last period of the study in upstream petroleum is not a typical Mark II, but rather a modified type in which a new class of dominant innovators emerge to cope with increasing technological complexity. We also argued that the dynamics of *technological opportunities* 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 analysed in combination with those of KBC 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 complexity could alter the Schumpeterian mode, while a rise (or decline) of technological opportunities tends to weaken (or 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 of the features of a Schumpeter Mark I mode. In contrast, when systemic complexity dominates the sector, the rise of technological opportunities is relatively more beneficial to incumbent and big companies (some of which are system integrators). This situation characterizes a (modified) 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 has progressively increased, leading to higher systemic complexity and knowledge cumulativeness of the sector in recent periods. This situation reinforced the relative position of big and incumbents compared to new firms and increased the barriers to entry. Put it differently, technical change was of a 'competence-enhancing' type (Tushman and Anderson, 1986) where incumbents have higher absorptive capacity (Cohen and Levinthal, 1989) 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. A number of service companies emerged and played the role of knowledge connectors or integrators, helping incumbents to cope with excessive complexity. In this sense, our historical accounts together with Maleki (2013) suggest that the innovation pattern in p3 is not a typical Schumpeter Mark II, but a modified version of it. While in early p1, operators were major innovators holding about 35% of all patents, in p3 integrated service companies become dominant innovators holding more than 40% of patents. In addition, the distinction between innovation size and firm size is important, as sizable innovators are not necessarily the biggest players in the sector. Our analysis evidences that rise of the large integrated service companies as dominant innovators, whilst oil operators were relatively weakened, and new oil operators made little headway as innovators.

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