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LOOKING FORWARD VIA THE PAST: AN INVESTIGATION OF THE EVOLUTION OF THE KNOWLEDGE BASE OF ROBOTICS FIRMS

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Abstract

The case studies described in this paper investigate the evolution of the knowledge bases of the two leading EU robotics firms - KUKA and COMAU. The analysis adopts an evolutionary perspective and a systems approach to examine a set of derived patent-based measures to explore firm behavior in technological knowledge search and accumulation. The investigation is supplemented by analyses of the firms' historical archives, firm strategies and prevailing economic context at selected periods. Our findings suggest that while these enterprises maintain an outward-looking innovation propensity and a diversified knowledge base they tend to have a higher preference for continuity and stability of their existing technical knowledge sets. The two companies studied exhibit partially different responses to the common and on-going broader change in the robotics industry (i.e. the emergence of artificial intelligence and ICT for application to robotics); KUKA is shown to be more outward-looking than COMAU. Internal restructuring, economic shocks and firm specificities are found to be stronger catalysts of change than external technology-based stimuli.

JEL Codes*: O33, L52, L63*
Keywords*: Innovation strategies, robotic industry, digital manufacturing, industrial robots*

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1. Introduction

Robotics has advanced significantly since the first mechanical systems were conceived. Several but related technological breakthroughs in engineering, computer science, information technology, and related sciences have expanded the robotics value proposition. Most recently, the continued development of more advanced technologies such as artificial intelligence (AI) and machine learning (ML), are providing new possibilities which could revolutionize the current industry (Estolatan et al. 2018).

Defining a robot remains difficult. Joe Engelberger, the visionary of the industrial robot, once said, "I can't define a robot, but I know one when I see one." There are various confounding technical factors that stand in the way of a definition (Wilson, 2015) and different informants have their own ideas (Pearson, 2015). However, a clear definition is crucial in the contemporary landscape and because of the increasing role that robots will play in future production. The robotics sector is considered one of the main drivers of digital manufacturing, an environment which promises to deliver not only automated but also intelligent modes of production (Schwab, 2017); robots are regarded as exemplar 'physical' components in the factories of the future.[1]

Not surprisingly, robots are central to conversations about next-generation manufacturing. Much of the excitement about robots among the public revolves around either a fascination with newer-generation robots' capabilities (such as interactivity, autonomy, and intelligence), or negative attitudes to their probable replacement of existing jobs. However, there is a notable absence of inquiry regarding the true capabilities of the firms that are expected to deliver these machines, i.e. the robot companies. There is a tendency to assume that these 'black box' will remain continuously innovative and competitive (Violino, 2016).

This paper tries to fill some of this gap by studying the evolution of the knowledge bases (and associable behavior) of the two leading European robotics firms, KUKA and COMAU, and developments within the sector more broadly. We are interested in these organizations' probable

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[1] In this paper, we focus mainly on robots in industrial manufacturing although we acknowledge that they are likely to have a major impact on the service industry. However, for reasons of space, we do not discuss this application extensively here.

responses to their contemporary environment. Are there historical antecedents that validate the expectation that robotics companies can deliver radical innovations easily? Can they be expected to revolutionize manufacturing completely? Are the latest attention-grabbing robots reported in the media representative of where the industry is now or might be in ten years' time? The answers to these questions could help to explain why development and innovation in digital manufacturing-related areas remain captive within select institutions and regions.

We rely on a theoretical framework based on an evolutionary and a 'systems' perspective on innovation to understand how firms' knowledge bases and accumulation strategies have changed over time. We operationalize our model through two case studies based on firm patents, historical records, and the broader industrial context. The analysis is centered on industry robots (IRs) – generally regarded as intermediate products within a broader user-producer interaction framework. While the importance of service robots (SRs) is increasing, here, we are more interested in industrial robots which currently comprise much of the industry.

The present study adds to the growing body of work which uses patent data to investigate firms' innovative behavior. The novelty of our contribution lies in the integrated framework we develop which combines a variety of objective patent-based analytical measures with rich case studies based on historical archives. This provides the reader with a holistic and detailed study of the evolution of firms' knowledge bases over time.

The remainder of the paper is structured as follows. Section 2 provides a brief theoretical review of firms' accumulation of technological knowledge. Section 3 describes the contemporary robotics landscape. Section 4 formulates the hypotheses and presents the methodology. Section 5 investigates the firm case studies. Section 6 provides a brief discussion and concludes.

2. Accumulation of technological knowledge and innovation strategies

By adopting an evolutionary approach, we view the enterprise as a behaviorally-constrained entity routinely seeking competitive advantage. It relies on established routines to reduce its internal tensions and to navigate its unfolding and uncertain market environment (Nelson & Winter, 1982). Firms routines are rooted in their existing technical knowledge base and they are likely to choose new combinations which approximate that knowledge base and allow the organization to accumulate a particular set of related capabilities (Dosi, 1988; Dosi, Nelson & Winter, 2001) which dictate a specific irreversible direction (Nishimura & Ozaki, 2017).

Sectoral systems approaches highlight latent stakeholders' feedback mechanisms and learning processes related to innovation activity. Internal-based learning dynamics such as 'learning-by-doing' (Arrow, 1962), 'learning-by-using' (Rosenberg, 1982) and Lundvall's (1985) 'learning-by-interacting' processes reduce costs to the firm and reinforce (or weaken) the existing structures to allow realization of overall system stability (or dissolution) (Fagerberg, 2006). The established routines and the underlying learning processes determine how the firm responds to the various emergent innovations which might be in the form of continuous improvements to existing goods ('incremental' innovations) or revolutionary changes which transform productions processes (or 'radical' innovations) (Fagerberg, 2006). Early Schumpeterian thought was predisposed particularly towards radical innovation, but more recent discourses have put progressive emphasis on incremental innovation (Rosenberg, 1976).

Relatedly, how the firm leverages its accumulated knowledge base to respond to a given set of possibilities is influenced also by the underlying opportunity costs and the environmental context of the choice. In the phases of decision making, the firm needs to balance exploitation and exploration activities: choosing between using its existing capabilities to act on the best alternative at the time or postponing and waiting for more uncertain (but potentially more fruitful) opportunities to emerge (March, 1991).

The firm's choices are confounded by a variety of dimensions related to its preferences and decision-making. These dimensions include the relational dynamics which influence the strategic allocation of resources (strategic control), the prevailing organizational process related to collective learning (organizational integration), the degree of financial commitment to innovative alternatives (financial commitment) (Lazonick, 2005), the ability of the firm to identify, integrate, and exploit new information (absorptive capacity) (Cohen & Levinthal, 1990), and the transferability and reuse (or 'stickiness') of the information (von Hippel, 1994).

Regardless of the innovation being introduced and the choices it involves, the literature highlights the value for the firm to maintain diverse technological capabilities – especially in formulating the appropriate responses to these stimuli. Investigation from an evolutionary perspective holds that innovative organizations are able to exploit a diverse set of technologies (Dosi, 1982; Nelson & Winter, 1982). Successful firms' comparative advantage is built on their organizational ability to combine large sets of technological competencies (Pavitt, 1991), and to incorporate new technologies into existing processes (Quintana-Garcia & Benavides-Velasco, 2008). The most resilient enterprises in the contemporary environment are those that are able to achieve a dynamic balance between these two inherently conflicting capabilities, both of which are necessary to maintain competitive advantage in both mature (through incremental innovation) and emergent (through discontinuous innovation) markets (Tushman & O'Reilly, 1996).

Several empirical studies examine these dimensions to understand the relationships among the above dynamic capabilities and firm performance. However, the results of these studies are mixed and inconclusive. Several scholars find a significant and positive relationship between the firm's dynamic capabilities and sales growth for both selected manufacturing industries and the sector as a whole (among others, Katila & Ahuja, 2002, Rosenkopf & Nerkar, 2001, He & Wong, 2004; Greve, 2007), for publicly-traded corporations (Uotila et.al., 2009), and high-technology industries (Cardinal, 2001). However, there is no consensus over which approach best distinguishes the individual effect of each aspect in relation to firm success. The meta-review in Gupta et al. (2006) describes the difficulty as stemming primarily from a lack of consensus on the methods that should be used and assumptions that need to be made to observe these capabilities.

There is another stream of work which focuses on identifying the technological and sectoral specificities related to innovation and knowledge accumulation (Fagerberg, 2006). Most propose sector-based categorizations such as Pavitt's (1984 external sources-focused taxonomy, while others distinguish firms based on their likely responses to various environmental stimuli (Benner & Tushman, 2003), or firm age (among others, Zahra, 1996 focuses on the differentiated innovative behavior of independent and corporate ventures while Rothaermel, 2001 studies entrant compared to incumbent firms). This literature strand provides a more nuanced differentiation among sectors, and in particular, a more detailed view of the propensities of 'high technology' industries. For example, this allows a clearer distinction between the electronics industry and the durable consumer goods sector (i.e. automotive) dynamics.

Of particular relevance for understanding the innovative dynamics in industries such as robotics, is the observation that the interactions between producers and external sources are valuable for directing the innovative process. For instance, in the case of the manufacture of electronic sub-assembly process equipment, Von Hippel (1977) notes several cases where the innovative activity is a collaborative work involving the manufacturer and the user. The literature underscores the importance of maintaining a diversified knowledge base in these industries as demonstrated in Brusoni, Prencipe, and Pavitt's (2001) investigation of multi-technology product manufacturers. Following Pavitt's (1984) taxonomy, the literature identifies these organizations as 'specialized suppliers' whose competitive advantage is built on a thorough understanding of users' needs. Pavitt (1984) adds that these manufacturers' innovations are often biased towards performance improvements such as better product design and reliability.

Again, drawing parallels with the evolutionary approach, these studies suggest that most user-producer interactions serve to stabilize the direction of technological development. As user-producer relationships strengthen, the innovative output increasingly becomes centered on a limited set of identifiable problems which need to be addressed (Rosenberg, 1976; Klevorick et al., 1995) which results in a 'natural trajectory' (Nelson & Winter, 1982). In that case, the industry risks being locked into a specific path through various self-reinforcing effects (Fagerberg, 2006). As relationships and dynamics stabilize, a 'dynamic inertia' can emerge which results in indifference toward new technical opportunities and user needs (Lundvall, 1985).

3. Methodology

We employ a qualitative case study approach using quantitative data to understand the development of the knowledge bases of KUKA and COMAU, the two leading European robotics firms. The cases were constructed by gathering data from patents, company reports, news archives and (in the case of COMAU) interviews. Patent data are used to trace the evolution of these companies' technological competences over 30 years from the mid 1980s to the mid 2010s.

To provide some background and identify the main characteristics and turning points in the evolution of these firms' knowledge bases, we provide a brief history of the robotics sector which informs our expectations related to the case analysis. This historical background is based on the data gathered from news archives, journal articles, industry reports, and intergovernmental analyses. For each decade, we present the salient market and technological developments.

Our focus on Europe is based on three main reasons. First, the presence of both industry-recognized robotics companies and dynamic national markets. The top Asian robotics producers are concentrated in Japan with some of Asia's largest markets (i.e. China, South Korea) hosting no sector-recognized robotics producers. Second, the availability of comparable cross-country patent data (from the European Patent Office - EPO). Three, the limited language constraints.[2] We applied similar selection criteria to our choice of the firm cases: they are industry-recognized 'top firms' and are headquartered in the largest European markets. Since the two largest robotics demand bases in Europe are in Germany and Italy (Estolatan et al., 2018), the research focuses on the German robotics producer KUKA AG, and the Italian COMAU SpA.[3]

Use of patent data is a long tradition in innovation studies such as those that examine inter- and intra-industry differences in innovation behavior (Scherer, 1965, Achilladelis, Schwarskopf, & Cines, 1990), or knowledge spillovers (Jaffe, Trajtenberg, & Henderson, 1993) across time (Jaffe & Trajtenberg, 1996, 1998) and regions (Maurseth & Verspagen, 2002). Despite some concerns[4] about the information provided in patents and its use, patents are used for economic research because they are 'better' than traditional measures for understanding inventive activity in the economy (Griliches, 1998). In particular, this research builds on a nascent sub-set of studies which rely on patent data to understand firms and their individual knowledge bases and knowledge

[2] Use only of EPO data provides consistency, reliability, and comparability across firms (Griliches, 1998). Also, the literature highlights the stability of EPO data over time and across countries (van Zeebroeck, van Pottelsberghe de la Potterie, & Han, 2006). Finally, while patent citations are susceptible to patent examiners' influence during the application process, previous work shows that European examiners are more stringent than their US American counterparts over their additions (Alcacer & Gittleman, 2006).
[3] While there are other more prominent and larger producers in Europe than COMAU, they are either headquartered in countries with no robust demand (i.e. Swiss firm Stäubli Holding AG), or are significantly involved in other lines of businesses (i.e. Swiss/Swedish ABB Group and its electrical systems production).
[4] See Griliches (1998) for a summary of patent-related issues. More recent critiques of patents are provided in Duguet and MacGarvie (2005) (inability of patents to characterize the learning process through imitation and reverse engineering) and Roach and Cohen (2013) (importance of patents for firms' strategic behavior). There are some concerns also about the patent application process, see Alcacer and Gittelman (2006) on examiner bias and Jaffe et al. (2000) on patents as a 'noisy' measure of knowledge spillovers.

accumulation.[5] Operationally, this means that patent data are interpreted as signals and traces of the firm's knowledge base and technological competencies. We believe that this makes our investigation less affected by the known limitations related to patent-based research.

We characterize firms' innovative behavior as follows: 1) technological diversification, 2) technological competencies, and 3) local-distant search tendencies. Table 4 presents these measures and their calculation. Technological diversification is a measure of the enterprise's range of technological capabilities. An index value close to 1 suggests that the firm exploits a wide range of technologies while a value of zero implies a focus on one specific technology. Following Patel and Pavitt (1997) we build a technological competencies matrix which combines revealed technology advantage (RTA) and patent share (PS) relative to the firm's overall patent portfolio estimations.[6] Last, we conduct a comparative analysis of the inclination for either external or internal search (which we treat as proxies for the firm's exploration and exploitation behaviors). We estimate them based on year-by-year comparison of the firm's institutional memory based on its patent stock during the previous five years, for any given year or stock-year (Rosenkopf & Nerkar, 2001; Katila & Ahuja, 2002).

Each index value is determined using a composite stock-year, aggregated from available data at the individual year level, such that each *stock year* is the total stock of knowledge during the previous five years. For instance, *stock-year* 1991 is the sum for the period 1987 to 1991. This approach reduces statistical noise and allows us to operationalize: 1) the cumulativeness of organizational knowledge, 2) the depreciation of knowledge (Argote, 2013), and 3) the bias towards recent knowledge based on organizational memory and individuals' memories (Alcacer & Gittleman, 2006). Accordiing to Katila and Ahuja (2002), other yearly aggregations yield significantly similar results. We construct a *stock-year* for each year from 1991 to 2015.

[5] Some examples in this tradition include Duguet and MacGarvie's (2005) use of patents and Community Innovation Survey (CIS) data in proving that patents parallel how knowledge flows in the organization, Stuart and Podolny's (1996) patent-based inquiry into Mitsubishi's rise in the Japanese semiconductor industry, Rosenkopf and Nerkar's (2001) citations- and IPC-based investigation of the various levels of firm exploration strategies in the optical disk industry, and Katila and Ahuja's (2002) study of firms' search behaviors in the robotics and chemicals sectors based on a combination of firms' patent citations, non-patent references, and product portfolios.
[6] A more detailed discussion regarding Patel & Pavitt's methodology is available in Appendix A.

The selected sample of patents for the analysis are patents granted by the EPO between 1987 and 2015. The data come primarily from Clarivate Analytics' Derwent Innovation database and are confirmed by comparable data from Bureau van Dijk's (BvD) Amadeus database. We constructed merger and acquisition (M&A) activity based on company reports and news archives to validate the patent data collected. This yielded patent counts of 355 for COMAU and 1,132 for KUKA. We extracted bibliometric information commonly used in the literature: e.g. number of IPC subclasses, both application and publication years, patent citations, and cited patents' first assignees. The patent count for COMAU is rather low (355), and thus, underrepresent the firm's total knowledge base. We show that this likely stems from COMAU's role as a subsidiary of the larger Fiat Chrysler Automobiles (FCA) Group whose R&D output is conducted in centralized laboratories. However, we believe that the sample represents the core technological knowledge of COMAU.

The quantitative patent analysis is complemented by a qualitative analysis of the evolution of the companies' activities during the same period. Financial, supplementary company information and M&A-related data are from the Amadeus database. Firms' annual reports, available online for the last 15 years or so[7] were analyzed to understand the firms' strategic decisions. Finally, we conducted a detailed analysis of professional news articles.

[7] In particular, FCA's 1999, 2001, 2004, 2005, 2007, 2008, 2009, 2013, 2014, and 2015 Annual Reports and KUKA AG's 2001, 2004, 2005, 2006, 2007, 2011, 2013, 2014, 2015, and 2016 Annual Reports are the primary sources of the supplementary data.

Table 4. Summary of patent data-based measures used in the research[8]

Name of measure	Formula	Variables	Patent data used	Notes
Technological diversification index	$1 - HHI = 1 - \sum_i p_i^2$	p_i is ratio of patents in technical field i.	4-level IPC subclass	Derived from the Herfindahl-Hirschman Index, equals zero if the firm works only on one technology and approximates unity if the firm's research activity covers a wide technological base. Patents assigned to multiple technical fields are treated as different applications.
Technological profiles	$TP = \frac{PS}{RTA}$	PS is IPC subclass' share in the firm's total IPC subclasses in a stock-year.	4-level IPC subclass	IPC subclasses are classified as core, niche, background, or marginal competencies which are defined as follows: core are distinctive technical competencies, niche are distinctive but relatively small technological fields, background are competencies to which the firm allocates significant resources but does not achieve relatively high advantage due to the size of the field, and marginal are activities to which the firm neither allocates sizeable resources nor achieves distinct advantages (Patel & Pavitt, 1997).
Revealed Technological Advantage	$RTA_{ij} = \frac{P_{ij} / \sum_i P_{ij}}{\sum_j P_{ij} / \sum_{ij} P_{ij}}$	P_{ij} is the number of patents of firm i that belongs to IPC class j applied with the EPO.	4-level IPC subclass	Data constraints dictated reliance on OECD data on all patent applications to the EPO from 1987 to 2014. Note that OECD statistics are fractional counts[9] of the entire EPO applications.
Local-distant knowledge search index	$Scope_{it} = \frac{nc_{it}}{tc_{it}}$ $SC_{it} = \frac{sc_{it}}{tc_{it}}$	nc_{it} is citations made in $firm\ ss_t$ but not in $firm\ ss_{t-1}$; tc_t is firms' citation stock; sc_{it} is self-citations.	Patent citations	Firm citation stock is calculated as: $firm\ citation\ stock_t = firm\ unique\ patent\ citations_t + firm\ unique\ patent\ citations_{t-1} + \cdots + firm\ unique\ patent\ citations_{t-4}$

[8] See Appendix A for a more extensive documentation of the methodology.
[9] The OECD uses a fractional count approach to distinguish patent applications by inventors of different nationalities; identifying patent 'nationality' allows a better approximation of countries' patent contributions. Although it is likely to differ from a straight count of EPO data, the effect is unlikely to affect our research since the focus of the analysis is on understanding the evolution of firm capabilities over time, and not absolute RTA values.

4. The contemporary robotics industry and its evolution since the early-1970s

The International Organization for Standardization (ISO) and the United Nations Economic Commission for Europe (UNECE), through the 2012 ISO-Standard 8373, loosely defines a robot as a reprogrammable, multifunctional manipulator designed to move material, parts, tools or specialized devices through variable programmed motions for the performance of a variety of tasks, which also acquire information from the environment and move intelligently in response. The International Federation of Robotics (IFR), the sector's main special-interest organization, and other national industry associations such as the US Robotics Industries Association (RIA) and the UK British Automation & Robot Association (BARA) have adopted similar definitions (BARA, 2017; IFR, 2017a; RIA, 2017).

Robots promise cost-efficiency and greater accuracy and reliability relative to human agents (ABB Group, 2016; PwC, 2017). They are able to perform tasks that are highly dangerous (i.e. nuclear power plant decontamination), repetitive, stressful, labor-intensive (i.e. welding), or menial for human agents. Currently, the IFR and the industry at large adhere to two classifications of robots: industrial robots (IRs) and service robots (SRs) (IFR, 2016a). An IR is an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes which can be either fixed in place or mobile for use in industrial automation applications (IFR, 2016b). A SR is a robot that performs useful tasks for humans or equipment excluding industrial automation applications (ISO 8373, 2012). As mentioned above, most of the succeeding sections focus on IRs because they represent (until recently) the core of the industry and are the building blocks of digital manufacturing.

Various recent but related developments in hardware and software technologies, academic research, and the industry itself have enabled sustained expansion of nascent sub-sectors, particularly those related to the digitization of production. Most prominent among these next-generation robots are interactive robots. These are expected to be viable in environments in which various forms of interactions with human agents take place, and are intuitive, easy-to-use, and responsive to user needs (Christensen et al., 2016). These next-generation robots promise human-machine cooperation beyond collision avoidance (Kruger, et. al., 2009), such that the flexibility and adaptability of human agents in complex tasks, and the consistency and productivity of machines in automated tasks can be achieved simultaneously in production (Michalos et. al., 2010).

In production in particular, the main anticipated sub-class of interactive robots is collaborative robots or co-bots. They were invented by Northwestern University McCormick School of Engineering professor Edward Colgate (with Michael Peshkin), and are mechanical devices which provide guidance through the use of servomotors with a human operator providing motive power (Krüger et al., 2009; Morris, 2016). In practice, what distinguishes a co-bot is its ability to provide direct power support to a human agent in a strenuous task while maintaining a high level of mobility (Lau, 2005). Although co-bots are employed mostly in manufacturing tasks, they are viable also for non-traditional applications such surgery (Delnondedieu and Troccaz, 1996).

4.1 A brief account of the evolution of the robotics industry

Roboticists date the emergence of the contemporary robotics landscape to mid-1950 to 1960 when Joseph Engelberger, of Consolidated Controls, together with the inventor Joseph Devol, launched the Unimate robot as a novel approach to automating production (Robotics Industry Association, 2018). Through Engelberger's efforts, in 1961 the Unimate robot was commercially applied in a General Motors (GM) assembly line in Trenton, NJ. Two years later, around 450 robots were being used in die casting activity across the carmakers' plant (Robotics Industry Association, 2018). However, technology adoption was slow, and Engelberger (1985) acknowledges that his company did not profit from it until 1975 because potential clients found it difficult at the time to find economic justification for installing robots (despite a clear value proposition and popular support). Engelberger attributed this primarily to the observation that manufacturing tends to be an inherently conservative activity in which institutional norms (including skepticism towards new technology and a preference for cheap human labor) are likely to prevail. It was not until strong labor unions and increased worker militancy in the US (Greenhouse, 1998) and Europe ca. 1970s (Tagliabue, 1982) which introduced innovative employee benefits (such as employer-financed pensions and cost of living adjustments), that car companies began increasingly to consider adoption of more automated modes of production.

At the same time of Unimate's first commercialization, much of the research was conducted in various university research laboratories such as Stanford, Massachusetts Institute of Technology (MIT), and Carnegie Melon University (CMU) (Kurfess, 2005). As Kurfess (2005) pointed out, most of these activities sought to improve machine intelligence and enable robots to respond in unstructured settings. Most prominent among these endeavors was Stanford student Victor Scheiman's 1969 Stanford arm, the first six-axis robot which demonstrated assembly capabilities thereby expanding potential robot applications (Corday, 2014).

The following decade witnessed the geographical spread of robotics beyond the US, as Engelberger introduced robotics to partners in Scandinavia and Eastern Europe (through Nokia, Finland) and Japan (through Kawasaki Heavy Industries) (Robotics Industry Association, 2018). Engelberger (1985) notes that the Japanese firms could be regarded as the catalyst for the broader adoption of robotics in manufacturing. He describes Japanese companies as enthusiastic about exploring the potential of the technology and being eager to apply the machines in their assembly lines. Comparable developments in the use of robotics in industrial applications were continuing also throughout Western Europe, by different organizations (our case companies).

In the 1970s and the 1980s material handling was a main area of application for robotics (Wallén, 2008). Wallén (2008) notes also that arc welding and assembly activities were emerging areas of application at that time, but both required better motor and control systems. Among the main user industries, Wallén (2008) observed that the automotive industry was the most valuable client ca. 1970s, with the metal sector another significant user.

Despite steady growth, employment of robots remained limited because of the substantial costs and inherent limitations of 'hard automation' technologies which require round the clock operations (Ayres & Miller, 1981). In the 1970s and 1980s, US manufacturing was predominantly batch activity meaning that production lines ran for extended hours or days. Prospective clients involved in batch-producing industries had concerns about the likely underutilization of the machines on the shop floor and any cost savings being mitigated by under-capacity (Carter, 1985).

The 1980s and the 1990s saw the steady expansion of robotics use in various industries, although the automotive industry remained the most significant – with GM the leading robotics purchaser at the firm level (Miller, 1989). The other major users of robots included home appliances, consumer goods, electronics, and off-road vehicles. Miller (1989) notes that there was substantial interest from the aerospace sector at the time, but most robotics projects were exploratory. By the late 1980s, there were industrial producers in Germany, Italy, Japan, and Sweden (Porter, 2011).

UNECE and IFR (1996, 1999) reports suggest that the 1990s saw relatively uneven growth of the industry. Global sales of robots decreased between 1991 and 1993, recovered up to 1997 and then declined in 1998. Major markets such as the US, Europe, and East Asia saw notable fluctuations in demand across the years, due to the economic crises during the 1990s. Throughout, the automotive industry continued to be the largest customer. Other significant robot application sectors at that time included off-road vehicles, electronics, food, pharmaceuticals, appliances, aerospace, and metal fabrication (UN-IFR, 1996). The latter half of the 1990s saw exploratory activities related to the transformation of IRs for service applications. Industry analysts attribute the viability of SRs primarily to the falling costs and increasing capabilities of the machines (UN-IFR, 1999).

Technology-wise, Engelberger (1985) noted that the commercially available robotics technology in 1985 was not markedly different from that available 20 years earlier. He points out that much of the expected improvements at the time could logically have been expected such as developments in vision and sense technologies. Later assessments echo Engelberger's views (UN-IFR, 2002). For instance, half of all operating robotics machines were used in welding activities – a distribution which had been stable for several years – and the second-largest application area was materials handling activities. Even more recent industry scanning suggests that contemporary robotics technology remains comparable to that available in the 1980s especially in its mechanical/hardware aspects (Estolatan et al., 2018).

Table 1 is based on IFR operational stock data for the period 1993 to 2015 and shows that demand distribution remained heavily concentrated, particularly in the four industries of automotive (38%), electrical/electronics (24%), metalworking (13%), and plastic and chemicals (13%). The fifthlargest, the catch-all category of all other manufacturing activities has an average share of only around 6% throughout the specified time frame. Demand did not pick up substantially in other industries.

Table 1. World robotics operational stock 1993 – 2015 share averages, by manufacturing sub-sector

Industry	Total Ave	SD	93 - '00 Ave	SD	01 - '10 Ave	SD	11 - '15 Ave	SD
Food and beverages	2.15	1.01	1.13	0.12	2.13	0.58	3.52	0.18
Textiles	0.20	0.08	0.29	0.01	0.18	0.05	0.11	0.01
Wood and furniture	1.13	1.23	2.21	1.69	0.76	0.16	0.31	0.03
Paper	0.33	0.05	0.34	0.03	0.36	0.03	0.28	0.03
Plastic and chemicals	12.67	1.08	12.69	0.69	13.46	0.56	11.52	0.67
Glass, ceramics, minerals	0.81	0.12	0.82	0.19	0.85	0.02	0.73	0.06
Metal	13.07	2.06	15.55	1.57	12.10	0.69	11.35	0.19
Electronics	23.92	4.69	29.73	1.81	20.03	1.95	22.03	1.17
Automotive	38.35	7.36	29.13	1.37	41.71	4.30	45.41	0.41
Other vehicles	1.47	0.87	2.48	0.36	1.21	0.55	0.57	0.01
Others	5.91	2.52	5.63	3.22	7.22	2.00	4.17	0.33

Source: IFR (2018)

As expected, the automotive sector has the highest demand for robots. In the period 1993 to 2000, automotive accounted for an average share of around 30%, and since then, carmakers have represented between 40% and 45% of demand. In contrast to the growing popularity of robots among carmakers, the electronics industry (the other major robots market) experienced a boom in demand during the 1990s (average 30%) which levelled out at the beginning of the 21st century to an average of around 21%. Year-on-year (YOY) analysis of the operational stock data (see Table 2) supports these increasing trends. Table 2 suggests also that there is steady annual growth in other applications such as food and beverages (both overall YOY and by-decade YOY calculations are indicative of increasing adoption). However, the broader trend hints at the persisting issues related to application on non-traditional areas. Apart from the food and beverage sector, all other sectors except the four previously identified show negative growth along our time frame. Positive YOY averages for non-traditional applications refer only to the period 1993 to 2000.

Table 2. World robotics operational stock 1993 – 2015 year-on-year (YOY) share averages, by manufacturing sub-sector

Industry	Total Ave	SD	93 - '00 Ave	SD	01 - '10 Ave	SD	11 - '15 Ave	SD
Food and beverages	5.92	7.16	4.31	11.75	9.23	2.68	2.95	2.03
Textiles	-3.67	6.34	0.06	5.79	-8.36	3.65	-0.05	6.59
Wood and furniture	-7.32	18.54	-6.66	33.98	-6.86	4.79	-10.47	9.05
Paper	-1.03	4.61	2.76	5.25	-1.48	3.31	-4.59	2.29
Plastic and chemicals	-0.93	3.93	1.17	4.07	-0.35	3.66	-4.13	1.87
Glass, ceramics, minerals	-1.33	9.79	-2.55	16.99	1.24	4.86	-5.13	1.72
Metal	-1.66	3.40	-3.89	2.61	-0.67	3.91	-0.70	2.54
Electronics	-0.81	5.07	-2.47	1.06	-3.41	4.59	4.68	2.75
Automotive	1.97	2.96	1.78	1.40	3.89	2.98	-0.53	1.09
Other vehicles	-5.16	10.37	2.57	13.35	-12.04	5.87	-2.15	3.61
Others	9.36	53.84	41.66	93.57	-6.53	7.86	-2.59	4.57

Source: IFR (2018)

Focusing on IFR delivered robots (robot sales) during the same period (see Table 3), we see increasing adoption of robotics in industrial applications but at a constant rate of growth which shows a doubling every 10 years or so. The data show also the drastic drop in demand for robots post-crises: demand decreased noticeably in years 1998 and 2009 following the 1997 Asian financial crisis and the 2008 financial crisis. In 1993, robots for use in manufacturing had an 18% share of total sales while those for general-purpose applications (apart from traditional agricultural and service applications) achieved an 82% share. By 2015, these trends had reversed – robots for manufacturing represented a 91% share and general-purpose robots an 8% share.

Table 3. World robotics delivered robots 1993 – 2015, by select years in select industries

Industry	**1993**	**1995**	**1997**	**1998**	**2000**	**2005**	**2008**	**2009**	**2010**	**2015**
Manufacturing	9,564	14,706	60,638	53,843	74,860	101,000	94,213	49,162	99,268	231,502
Unspecified applications	43,724	54,507	19,873	14,331	23,184	18,542	18,158	9,938	20,088	20,007
All Industries	53,409	69,260	81,675	69,025	98,667	120,100	112,972	60,018	120,585	253,748

Source: IFR (2018)

Table 4 summarizes developments in the robotics industry. Overall, its history presents a picture of a high-technology sector struggling constantly to maintain market stability (particularly in terms of its relationship to mostly conservative manufacturing sector markets) and to introduce sectoral dynamism (by introducing new robot-related technologies intended to lead to new products and new market opportunities). We observe several examples of diversification efforts and many instances of failed experimental initiatives aimed at changing the value proposition in a sector and relationships to target markets.

Table 4. Salient developments in the robotics industry

Period	Development
1950-1959	Joseph Engelberger & Joseph Devol launch the Unimate robot as a production automation solution.
1960-1969	Unimate robots start to be integrated in General Motors' assembly lines; various universities (i.e. Stanford, MIT) continue to research robotics technologies.
1970-1979	Robots are introduced in international markets particularly in Scandinavia, Eastern Europe, & Japan; comparable advances are achieved in Western Europe (i.e. Germany, Italy).
1980-1989 (until early-1990s)	Robots are being used increasingly in other industries (such as home appliances, consumer goods, electronics, off-road vehicles), although carmakers remain the main market; industrial robot producers are established in Germany, Italy, Japan, and Sweden.
1990-1999	Robotics industry experiences uneven growth although it maintains high exposure in the automotive sector; experiments in service applications begin.
2000-2009	Robots remain in demand by the car making sector and increasingly the electronics sector; robot use in non-traditional applications continues to be difficult.

Nevertheless, we think that recent big data, data storage, computational capacity, and algorithm developments are accelerating advances in artificial intelligence and promise radical changes to sector dynamics. The second part of the 2010s has seen daily announcements of new futuristic fully interactive robots produced by technological startups and successful development of interactive robots (particularly co-bots). These have been introduced in manufacturing and are allowing more extensive human-robot collaboration which should lead in turn to productivity increases (Shah et al., 2011). Early adopters - mostly car manufacturers – have already realized gains (Nisen, 2014; Luxton, 2016; Zalecki, 2016). These next-generation robots are expected to be a significant driver of industry growth in the future (Lawton, 2016a; Universal Robots, 2016) depending on whether their diffusion is accompanied by a radical reorganization of the factory.

We think that this sudden influx of new technologies in highly complementary industries will lead the industry and its enterprises to increase their technological diversification (allowing it to better realize the more sophisticated robotics products), and expand their innovation strategies (since these new technologies require that they access other companies with expertise in these emergent digital technologies). Thus, we expect significant changes to firm behavior and associated changes to the knowledge bases of our focal firms from the mid 2000s.

5. Accumulation of technological knowledge: the cases of COMAU and KUKA

To examine the case firms' knowledge accumulation in terms of diversification and specialization of technological knowledge over time, we split our analysis into two parts. Each case study begins with archival analyses of company reports, news archives, and financial databases, and identification of organizational milestones. Next, we discuss the set of derived patent-based measures for each firm, emphasizing structural breaks and shifts in trends in relationship to these firms' historical evolution. Similarities and differences in knowledge bases and accumulation strategies are investigated in detail by analyzing the firms' broader socio-economic environment.

5.1 COMAU SpA

COMAU, derived from the acronym COnsorzio MAcchine Utensili (consortium of machine tools), was established in 1973 by Torino-based engineers who had been involved in building the Russian Volga Automobile plant. The company was first partly and then fully owed by FIAT, it was engaged in producing industrial automation and advanced manufacturing systems. COMAU was instrumental in helping FIAT transform its manufacturing sites into automated factories through the development and introduction of its highly flexible Robogate systems (Camuffo & Volpato, 1996). In the 1980s, COMAU leveraged this expertise to enter the North American market (through its affiliate Comau Productivity Systems) and to work with German mechanical engineering TRUMPF Group on the development of laser robots. From the 1990s to 2000, COMAU expanded beyond servicing FIAT's plants and its North American partners (mainly, General Motors at the time) and established a presence in other European countries, South America, and Asia. It worked on the development of automation solutions and equipment maintenance services for related industries such as aerospace, heavy vehicles, railways, and renewable energy. Some notable acquisitions made by COMAU in that period include Renault Automation France, GermanINTEC GmbH, and the North American bodywork systems manufacturer Progressive Tool and Industries Co. (PICO). At the beginning of the 21st century, COMAU was a high-technology enterprise which offered an integrated value proposition (from automation solutions to aftermarket maintenance) to its customers. Unlike other robotics companies it offered a complete hardware and software proposition with a proprietary software component.

Table 5. COMAU SpA financial highlights 2008 - 2015, in thousands EUR

	2008	2009	2010	2011	2012	2013	2014	2015	Average
Current assets	NA	NA	NA	NA	NA	NA	NA	NA	NA
Total assets (TA)	NA	NA	NA	NA	NA	NA	NA	NA	NA
Non-current liabilities	NA	NA	NA	NA	NA	NA	NA	NA	NA
Current liabilities	NA	NA	NA	NA	NA	NA	NA	NA	NA
Total liabilities (TL)	NA	NA	NA	NA	NA	NA	NA	NA	NA
Operating revenue	1,123,000	728,000	1,023,000	1,402,000	1,482,000	1,463,000	1,550,000	1,952,000	1,340,375
Period P/L (Net income) / EBIT	NA	(32,000)	(6,000)	(120,000)	33,000	47,000	60,000*	72,000*	(15,600)
No. of employees	11,445	11,708	12,216	14,457	NA	NA	NA	~9,000**	NA
Current (working capital) ratio	NA	NA	NA	NA	NA	NA	NA	NA	NA
TL/TA ratio	NA	NA	NA	NA	NA	NA	NA	NA	NA

Source: Amadeus database (2018)
Notes: R&D expenses includes capitalized R&D and R&D charged directly to income statement.
*EBIT Report was adjusted in 2013 to reflect subsidiary's adjusted EBIT.
** Estimated employees' number from recent annual reports

Company documents suggest that COMAU experienced some difficulties in the 2000s. In 2004, the firm conducted some minor restructuring which resulted in its Mirafiori capabilities (i.e. service and die) being transferred to the parent FIAT Auto and FIAT-GM power train, and a significant part of its total servicing and maintenance operations distributed to sister companies such as IVECO, Magneti Marelli, and CNH. By the third quarter of 2006, the FIAT Group had imposed on COMAU a significant restructuring program. This took approximately two years and resulted in down-sizing and divestments (particularly, COMAU France's engineering business, COMAU's South African businesses, and COMAU subsidiary GermanINTEC, and the transfer of Turin's engineering division to the affiliated Elasis Group). At the same time, FIAT consolidated its research efforts into two non-COMAU subsidiaries: 1) Centro Ricerche FIAT (Piemonte) and 2) Elasis (Southern Italy) in 2007. In 2008 when FIAT and Chrysler merged into the FIAT Chrysler Automobiles (FCA) Group, COMAU increased its exposure to the Group's companies. It took on responsibility for modernizing the Group's (particularly Chrysler's) operations. A significant proportion (25%-30%) of COMAU's sales are made by the Group's companies. Currently, COMAU is involved mainly in powertrain metal cutting systems, mechanical assembly systems and testing, innovative and high-performance body welding, and assembly systems and robotics.

The most recent (although limited) financial statistics[10] for 2008 to 2015 (see Table 5) provide evidence of the firm's restructuring. The first half of the seven-year period is characterized by negative net income. Only in 2012 did COMAU begin to reap the benefits of its strategy and become profitable. Employee numbers in the first half of the period were around 12,000 on average; by 2018 COMAU had around 9,000 employees spread across 17 different countries. Table 6 summarizes COMAU's main developments.

Table 6. COMAU SpA salient developments throughout its organizational history

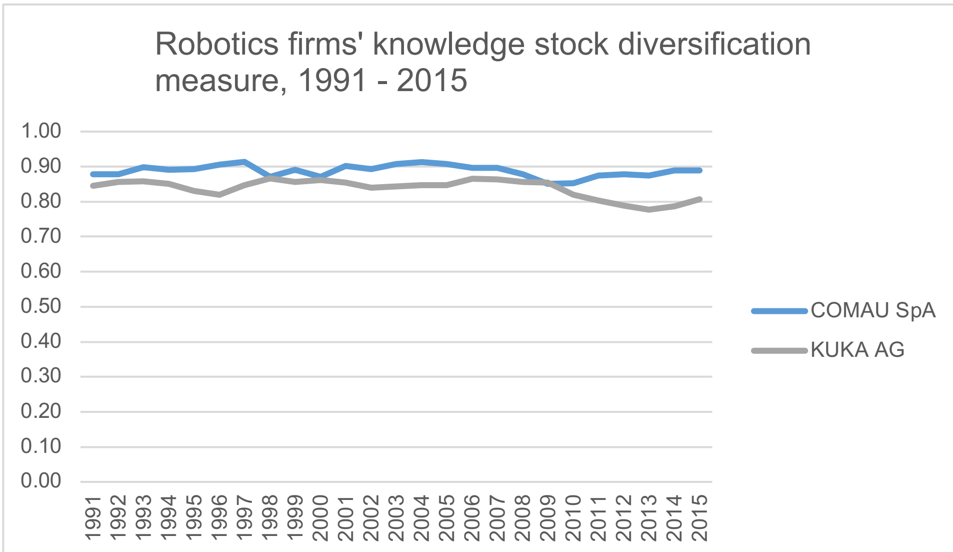
Period	Development	Key collaborators	Key acquisitions	Key divestments
1973	COMAU is established by Torino-based engineers as an automation systems provider for the FIAT Group.	FIAT Group	NA	NA
1980s	COMAU begins development of advanced robotics (i.e. laser robots); COMAU enters the North American market.	FIAT Group; TRUMPF Group	NA	NA
1990s	COMAU leverages its capabilities in other industries (i.e. aerospace, heavy vehicles, etc.); COMAU expands and enters markets in other European, South American, and Asian countries.	FIAT Group	Renault Automation France; germanINTEC GmbH; Progressive Tool and Industries Co.	NA
2004	COMAU undergoes a corporate restructuring.	FIAT Group	NA	Service & die capabilities; servicing & maintenance operations
2006 (Q3)	COMAU undergoes a significant corporate restructuring.	FIAT Group	NA	COMAU France; COMAU South Africa; germanINTEC; COMAU Italia's Turin engineering division
2007	FIAT consolidates its R&D efforts across its subsidiaries.	FIAT Group	NA	COMAU's several R&D units
2008	COMAU increases its exposure to the FIAT Group's (now FCA Group) operations.	FIAT Chrysler Automobiles (FCA) Group	NA	NA

COMAU's combination of patent-based measures are aligned to the above developments. Our analysis suggests that: a) the firm maintained its high technological diversification from 1991 to 2015 (see Figure 1), b) there was a marked reduction and shift in its technology mix around the

[10] More detailed financial data are available for COMAU's operations in Italy during the same period. See Appendix B for the reference.

mid-2000s (see Figure 2), and c) there was a behavioral shift in its local knowledge vs. distant knowledge search around the mid-2000s (see Figure 3).

Figure 1. COMAU SpA and KUKA AG diversification measures, stock-years 1991 – 2015



COMAU's technological profile in the period 1991 to 2015 went through significant changes although some of its core competences remained unaltered (see Figure 2). On average, among the firm's 73% of technologies that can be classified according to the Patel-Pavitt matrix, 28% are *core* technologies, 7% are *niche*, 14% are *background*, and 25% are *marginal technologies*. The 'technology mix' shift shows substantial reductions in *marginal* and *background* technologies and a notable consistency in *core* capabilities in metal forming machinery and machine tools (B23K & B25J) and motor vehicles (B62D). In addition, we observe capacity-building in computing and electronics manufacture particularly in measuring instruments (G05B), and evolution from a *background* competency to a *core* competency by 2014.

Figure 2: COMAU SpA Technology Profiles 1991 / 2014 (IPC and NACE economic activity)

Stock-year 1991

Background

IPC Subclass	*Economic activity*
G05B	instruments and appliances for measuring
B21D, B23Q	metal forming machinery & machine tools; machinery & equipment
G01B	computer, electronic, and optical products

Core

IPC Subclass	*Economic activity*
B23K	fabricated metal products, except machinery
B25J	metal forming machinery & machine tools; machinery & equipment
B62D	motor vehicles

Marginal

IPC Subclass	*Economic activity*
B30B	fabricated metal products, except machinery
G01D	instruments and appliances for measuring
B60J	motor vehicles
C09J	other chemical products
B65G	other general purpose machinery
H02G	wiring and wiring devices
E04H	specialized construction activities

Niche

IPC Subclass	*Economic activity*

Stock-year 2014

Background

IPC Subclass	*Economic activity*
B65G	machinery & equipment

Core

IPC Subclass	*Economic activity*
G05B	instruments and appliances for measuring
B23K, B23P, B25J	metal forming machinery and machine tools
B62D	motor vehicles
B62B	Other manufacturing

Marginal

IPC Subclass	*Economic activity*
F16H	general purpose machinery
B23Q	metal forming machinery and machine tools
B05B	other general purpose machinery
E04H	specialized construction activities

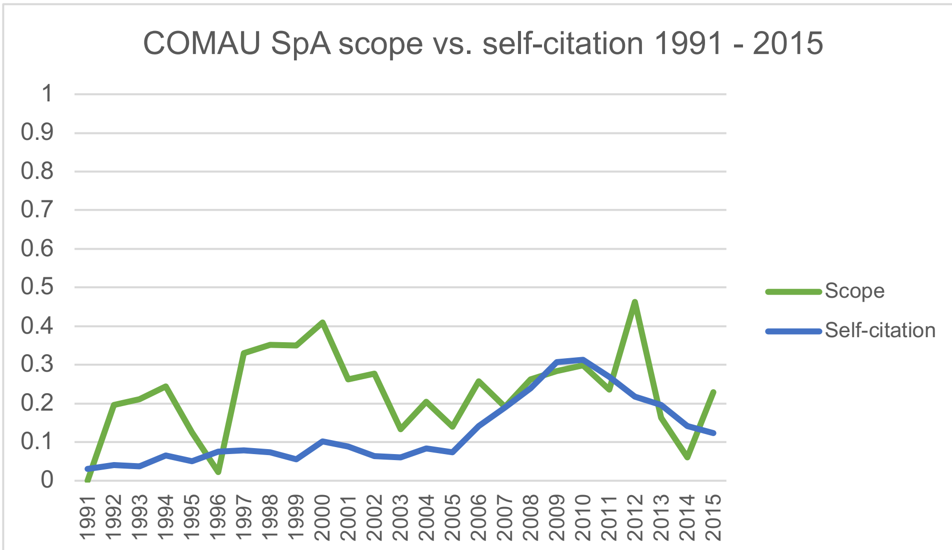
Niche

IPC Subclass	*Economic activity*
B21D, B21J	metal forming machinery and machine tools
B05C	other special purpose machinery

For the mapping from IPC sub-classes to NACE activities, we follow Van Looy, et. al's (2014) concordance table.

Regarding the local-distant knowledge search (see Figure 3), COMAU's behavior over 25 years is market by notable shifts and a few trends. Overall search tendency is relatively consistent, with roughly a quarter of new knowledge added to the total knowledge base on average. Interestingly, there was a marked shift around the mid-2000s when COMAU substantially increased its self-citation intensity; self-citation behavior began to decrease by 2011.

Figure 3. COMAU SpA search scope and self-citation measures, stock-years 1991 – 2015



5.2 KUKA AG

KUKA started when Johann Josef Keller and Jakob Knappich founded "Acetylenwerk für Beleuchtungen in Augsburg" back in 1898. KUKA is derived from the abbreviation the founders often used in their telegrams i.e. the initial letters of “Keller und Knappich Augsburg.” The 120-year old company was initially a producer of lighting for Augsburg households and streets but soon expanded into welding-related activities including welding technologies and related activities such as cutting. It accumulated competencies to enable industrial-scale production, particularly for municipal vehicles and consumer appliance manufacturing. It also developed capabilities in industrial automation.

Industrial automation capabilities have become an increasingly important part of KUKA’s core offer since the merger with Industrie-Werke Karlsruhe AG in the early-1970s to form IWKA AG. In addition, the new enterprise entered the areas of packaging machinery, textile engineering, control technology, metal forming, and machine tools. By the 1980s, the former KUKA became

IWKA and transformed into a holding company for various (loosely) interrelated businesses focused on environmental, welding, and defense technologies. The succeeding years saw KUKA (IWKA AG at this time) continue to develop its competencies and market expansion (particularly in North America). The most important acquisitions during that period were KUKA's acquisitions in 1999 of the German technology enterprise Rheinmetal Group and the Anglo-American BWI Group. This strengthened the firms packaging capabilities. At the start of the 21st century, KUKA was a broad-based technology group involved primarily in production (welding), manufacturing (automation), process (controls and measurement), and packaging technologies for an extensive set of industries.

Apart from this, KUKA has invested continuously in robotics-related technologies over the years. It was responsible for the installation of robotic welding transfer lines in Daimler-Benz's plants in 1971. In 1973, KUKA introduced FAMULUS, claiming that it was the first industrial robot with six electromechanically driven axes. In the 1990s, KUKA embarked on the introduction of open-source control mechanisms for its automated machines. Throughout this period, robotics continued to be important for the firm's development.

KUKA's annual reports indicate that operational risks and an unfavorable economic climate triggered the firm restructuring in the mid-2000s. As early as 2000, KUKA had begun to sell defense-related technologies. In 2004, it began an extensive divestment process which involved the sale of its non-core businesses and process technologies. Over the next three years, KUKA continued to make further divestments including severance with the machining providers EX-CELL-O Group and the Boehringer Group, and the standard machine tools producer GSN Maschinen-Anlagen-Service GmbH (KUKA AG, 2006). It completed its divestments by severing its ties to the Bopp & Reuther-affiliated VAG-Armaturen GmbH (KUKA AG, 2004) and the RMG group (natural gas distribution measurement activities) (KUKA AG, 2005). In 2007, KUKA sold off all of its companies involved primarily in packaging technologies (KUKA AG, 2007). KUKA's employment dropped from nearly 12,000 in 1999 to just over 5,000 in 2007. However, in this period KUKA refocused on robotics and production systems. When it was reborn from IWKA AG to KUKA AG once more, the company had only two business segments: robotics and automation systems. This distinction among is operations remained stable to 2013. Robotics became a central component in KUKA's business strategy after (and even during) its restructuring.[11] The company's intent was to deepen and leverage its robotics expertise to apply a more diverse set of non-automotive industries including plastics processing, logistics, medical technologies, and food and food processing. The change in its executive management in 2009 increased the focus on these goals and resulted in more aggressive marketing of robotics for potential non-automotive applications (McGee, 2017).

Table 7. KUKA AG financial highlights 2008 - 2015, in thousands EUR

	2008	2009	2010	2011	2012	2013	2014	2015	Average
Current assets	697,850	555,789	821,470	911,400	959,400	1,150,800	1,309,100	1,689,200	1,011,876
Total assets (TA)	865,478	726,221	984,738	1,078,000	1,137,400	1,377,100	1,979,500	2,381,700	1,316,267
Non-current liabilities	274,812	293,113	398,188	380,800	405,900	502,500	517,200	631,600	425,514
Current liabilities	377,132	272,283	388,465	444,800	434,000	495,500	921,200	1,017,600	543,873
Total liabilities (TL)	651,944	565,396	786,653	825,600	839,900	998,000	1,438,400	1,649,200	969,387
Operating revenue	1,294,215	927,119	1,108,847	1,478,600	1,771,000	1,806,000	2,105,500	2,988,900	1,685,023
Period P/L (Net income)	30,552	(75,812)	(8,566)	29,900	55,600	58,300	68,100	86,300	30,547
No. of employees	5,815	5,811	5,629	6,140	6,830	7,477	11,504	12,355	7,695
R&D expenses	33,711	35,565	29,537	37,700	42,600	59,700	78,200	105,400	52,802
Current (working capital) ratio	1.85	2.04	2.11	2.05	2.21	2.32	1.42	1.66	1.96
TL/TA ratio	0.75	0.78	0.80	0.77	0.74	0.72	0.73	0.69	0.75

Source: Amadeus database (2018)

Some of its most significant post-restructuring robotics-focused milestones include the establishment of the Advanced Robotics section (KUKA laboratories) within its robotics division and a foray into collaborative robots through its lightweight robot (LWR) developed in 2011. In the context of M&As, KUKA's strategy was aimed at strengthening its core divisions. Its acquisitions (all completed in 2014) include Reis Group which extended KUKA Systems Division's capabilities in the cell business for general sectors; Alema Automation SAS which gave KUKA Systems competencies in industrial automation for aircraft manufacture; and a stake in FAUDE Automatisierungstechnik GmbH a production and process automation provider specialized in human-robot collaboration. Its most important merger (in 2014) was with Swisslog Holding AG, a one hundred years old Swiss robotics company specialized in automation solutions for warehouse logistics (particularly the demand segments of e-commerce, pharmaceuticals, and temperature-controlled foodstuffs) and healthcare. KUKA integrated Swisslog as a subsidiary, completing the process in 2015. Recent management discussion confirms KUKA's ambition to

[11] 2007 also saw the introduction of KUKA's (and the world's) largest and strongest IR, the KR Titan.

leverage its robotics and industrial automation know-how to serve a range of industries, including automotive, aerospace, electronics, FMCG, metals, energy, healthcare, and e-commerce. KUKA's more recent patent-based technological profile demonstrates the increased scope of the firm's knowledge base and diversification into potential new robotics user industries (with different technological characteristics and requirements) such as warehouse automation and healthcare.

Table 8. KUKA AG salient developments throughout its organizational history

Period	Development	Key collaborators	Key acquistions	Key divestments
1898	KUKA is established by Johann Josef Keller and Jakob Knappich as an Ausburg lighting & welding company.	NA	NA	NA
1970s	KUKA merges with Industrie-Werke Karlsruhe AG to form IWKA AG as an industrial automation firm; KUKA develops FAMULUS, the first six-arm IR.	Industrie-Werke Karlsruhe AG	NA	NA
1980s	KUKA (now IWKA AG) expands its operations to other industries (i.e. packaging machinery, textile engineering, control technology, metal forming, and machine tools).	NA	NA	NA
1990s	IWKA AG becomes a holding company for interrelated businesses focused on environmental, welding, & defense technologies; IWKA AG expanded to international markets (i.e. North America).	NA	Rheinmetal Group; BWI Group	NA
2000	KUKA sells its defense-related technologies	NA	NA	Rheinmetal Group
2004-2006	KUKA sells its interests in non-core business operations	NA	NA	EX-CELL-O Group; Boehringer Group; GSN Maschinen-Anlagen-Service GmbH; Bopp & Reuther-affiliated VAG-Armaturen GmbH; RMG Group
2007	KUKA re-establishes itself as KUKA AG; KUKA completes its divestment strategy and refocuses on its core competencies in robotics and production systems.	NA	NA	Packaging technology unit
2009	KUKA undergoes a change in its executive management.	NA	NA	NA
2014	KUKA undergoes an aggressive M&A strategy to strengthen its core businesses	NA	Reis Group; Swisslog Holding AG;	NA

Financial data for 2008 to 2015 (see Table 7) exhibit small but discernible traces of the KUKA restructuring process (much of which happened in the preceding years). The statistics highlight also the periods of relative stability and succeeding abrupt change which KUKA experienced with the change in its executive management in 2009. The years 2008 and 2009 (and to a lesser extent

2010) suggest an overall contraction of the firm (reductions in R&D expenses and employee counts persisted until 2010). Thereafter, organizational growth remained minor; KUKA focused on reducing its losses and improving its liquidity. The effects of the management changes began to materialize around 2013 as significantly increased current assets, current liabilities, and R&D expenses and flat profitability growth. There were sizeable increases across all the metrics in the years that followed although the firm's high liquidity and low leveraged character had begun to erode by 2014. In 2018, KUKA had around 14,000 employees spread across 39 different countries. Table 8 summarizes KUKA's salient developments.

Similar to COMAU, KUKA's set of patent-based measures show shifts and breaks in line with the above narrative. Our analysis suggests that: a) the firm maintained its high technological diversification from 1991 to 2015 (see figure 1), b) experienced a marked reduction and shift in its technology mix in the mid-2000s (see figure 4), and c) experienced a behavioral shift in its local vs. distant knowledge search around the mid-2000s (figure 5).

Figure 4: KUKA AG Technology Profiles 1991 / 2014 (IPC and NACE economic activity)

Stock-year 1991

Background

IPC Subclass	*Economic activity*
B25J	metal forming machinery and machine tools
B62D	motor vehicles
B08B	other special purpose machinery

Core

IPC Subclass	*Economic activity*
B23K, B23P	metal forming machinery and machine tools
F41A, F41F	weapons and ammunition

Marginal

IPC Subclass	*Economic activity*

Niche

IPC Subclass	*Economic activity*

Stock-year 2014

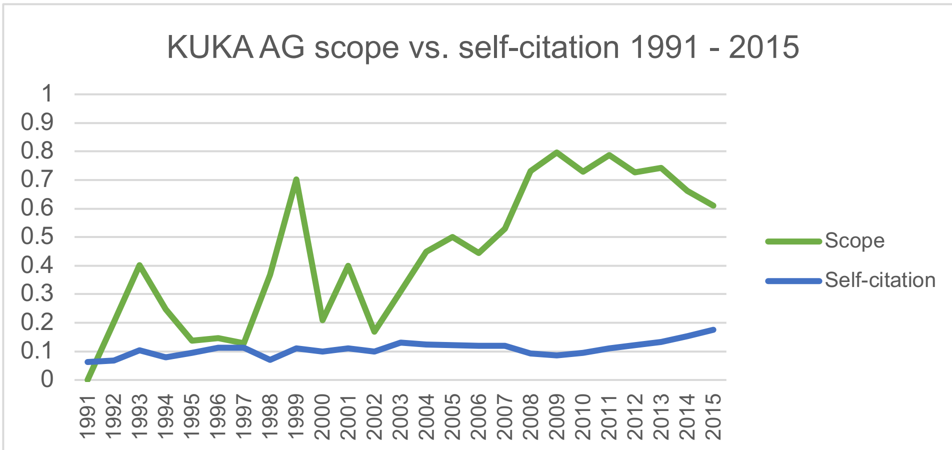
Background		Core	
IPC Subclass	*Economic activity*	*IPC Subclass*	*Economic activity*
A61B	medical and dental instruments and supplies	G05B	instruments and appliances for measuring
		B23K, B23J	metal forming machinery and machine tools
		B65G	other general purpose machinery
Marginal		**Niche**	
IPC Subclass	*Economic activity*	*IPC Subclass*	*Economic activity*
F15B	general purpose machinery	G05D	general purpose machinery
G01C, G01D, G01L, G01R	instruments and appliances for measuring	B21D, B21J, B23P, B23Q	metal forming machinery and machine tools
G01T	medical and dental instruments and supplies	B61B	other general purpose machinery
B23B	metal forming machinery and machine tools	B05C, F16P	other special purpose machinery
B60J	motor vehicles	A63G	Other manufacturing
B66F	other general purpose machinery		
B05D	other special purpose machinery		
G09B	Manufacturing N.E.C		

Our mapping of IPC sub-classes to NACE activities is in line with Van Looy's (2014) concordance table.

The selected technological profiles of KUKA from 1991 to 2015 (see figure 4) demonstrate the richness of its technical capabilities. Among the enterprise's 66% technologies classifiable in the Patel-Pavitt matrix, 18% are *core*, 11% are *niche*, 14% are *background*, and 23% are *marginal*. The technology mix shift in the mid-2000s constituted an extensive change and involved substantial reductions in its *background* and *core* technologies. However, there was a marked increase in its *marginal* and *niche* technologies. KUKA built on its capacity in measurement and computing capabilities with measurement instruments and appliances (G05B) becoming a *core* competence. Finally, it can be seen how certain technologies became irrelevant to the company's capabilities. In stock-year 1991, the company had technical strengths in fabricated metal production and military production. Over time, these capabilities lost their significance and finally became obsolete and resulted in the sale of its military activities.

In the context of the firm's propensities for local or distant knowledge search (see figure 5), the analysis does not support the idea of exploitation and exploration as two ends of a continuum. Rather, KUKA employed both strategies when appropriate – from the early 2000s to the present there has been an increase in the scope of the external search coupled with relatively stable self-citation behavior (10% of citations). This confirm that the diversification strategy related to M&As was aimed at achieving a strategic repositioning of the KUKA knowledge base in robotics areas distant from its traditional knowledge.

Figure 5. KUKA AG search scope and self-citation measures, stock-years 1991 - 2015



5.3 The mid-2000s restructuring among robotics firms: was this coincidental?

The technological and behavioral shifts that occurred in COMAU and KUKA around the mid-2000s require further investigation. Were they the result of internal deliberations or the products of an external shock? Looking into the evolution of the automotive sector, the long-standing primary market for automation, suggests that the crises and restructuring of the automobile industry had a major demand shock on the robotics sector.

The state of the global automotive sector in the early 2000s depended mainly on robust demand from the Americas and Western Europe (which were already at a peak) since the Asian and other emerging markets were only beginning to emerge (UK House of Commons, 2004). Among these markets, the US was the most valuable and included some of the world's largest car manufacturers and significant demand for vehicles. For robotics firms, the US was equally important because its car companies maintained significant capital spending plans and had a strong inclination for industrial automation (FIAT Group, 2005; KUKA AG, 2004). While Western Europe was also valuable, the robotics market was already mature and had only modest room for growth (although at the time high levels of growth were expected in the new EU Eastern Europe countries) (KUKA AG, 2004).

This sectoral dependence meant that the demand crunch which occurred in US car industry affected the robotics manufacturers. This crunch was due to several factors including over-production of vehicles (resulting in oversupply in the market), declining car affordability, shifting consumer preferences from new to used vehicles, and continuing entry by Asian car manufacturers (even in segments traditionally dominated by American car companies) (Carson *in* Klier, 2004; US International Trade Administration, 2005; Reynolds, 2017). The resulting increased competition steadily eroded the high profit margins which US car makers previously had enjoyed. This led to the prioritization of cost reductions, the closing and restructuring of manufacturing plants, cutbacks to capital spending, and the postponement of automation plans (UK House of Commons, 2004; US International Trade Administration, 2005).

The European market was unable to balance the effects of this contraction because the concurrent rapid rise in oil prices offset potential increased demand for cars in continental Europe (European Parliament Director General for Research, 2001; KUKA AG, 2005). Furthermore, commodity super-cycles (mainly brought about by China's significant demands for such goods) led to skyrocketing of prices of essential inputs (i.e. steel) for robotics production (Magne & Frécaut, 2009).

These factors in combination suggest that the mid-2000s was a 'perfect storm:' robotics companies were plagued by both supply- and demand-side pressures. Shrinking demand in traditional markets and rising business costs forced robotics producers to rethink their operations. While opinions regarding the vulnerability of the business to business cycles vary (see Management Discussion in COMAU's Annual Report 2004 and KUKA AG's Annual Report 2004 for contrasting perspectives), most automation solutions providers decided it was necessary to diversify their demand portfolios and increase the value propositions of their products.

6. Discussion and conclusions

Our objective in this paper was to understand the evolution of contemporary, high-technology robotic companies' knowledge base, the development of their technical capabilities, and the shifting in their knowledge accumulation strategies over time. We were interested in how the companies prepared to cope with trends such as the emergence of interactive robots and digital manufacturing.

The methodology we adopted offers the reader a variety of evidence to allow a better understanding of the evolution and accumulation strategy employed by European incumbent robotics firms with regard to their knowledge base. We think that a nuanced understanding of past actions is needed to predict advances in an industry which is likely to become the foundation for digital manufacturing developments and a large number of service industries (not discussed in this paper). Our literature review and study of the robotic industry's evolution portray incumbent robotics firms as conservative organizations deploying incremental knowledge accumulation strategies (resulting in incremental growth in their knowledge bases) that is heavily influenced by the requirements of users. On the other hand, recent developments in the sector more broadly have opened the way to new high-technology companies that are seemingly able to explore opportunities and offer radical innovation, thus creating new markets. Between these two, which of these portrayals best captures the behavior of the two leading robotics companies in Europe? How did they respond to challenges to their competitive advantage? Did they employ similar innovation strategies?

The case studies suggest that the truth lies somewhere in between. Our analysis shows that the studied firms recognized the need to adapt although the shifts were gradual. Based on stylized facts derived from patent data, it is clear that competency shifts take time and that accumulated capabilities often are retained. While we have only superficially captured the evolution and adoption of background and niche technological competencies in our case firms, we show that there is relative consistency in their development of core competencies. Company archive material suggests also that external economic shocks and market expansion were stronger triggers of organizational change.

Our results indicate that high-technological diversity is a core feature of large European robotics firms. There is no evidence to suggest that they were inclined to increase this diversity further when a new technological opportunity arose. Also, matching of these data to the firms' technological profiles indicates that this high mix is based mostly on a large set of *marginal* competencies and a smaller set of *core* competencies. Together, these support the idea that robotics firms' capability-building is aimed more at maintaining absorptive capacity than increasing their technical skills (which the 'learning-by-doing' dynamic predicts). Firms' current knowledge bases seem appropriate not for pursuing revolutionary innovations but for guaranteeing comprehensive developments in other technological areas. These observations can be compared to recent research which shows that the robotics sector requires its actors to be highly relational and to have capabilities that bridge across disciplines, industries, applications, and knowledge (Leigh & Kraft, 2016). Also, the stylized facts suggest that core competence-building (i.e. computer-related capabilities) takes a significant amount of time.

The study provides only very limited support for our predictions about an *exploitation-exploration tradeoff* where firms (such as contemporary robotics companies) increase their distant search (exploration) and decrease their local search (exploitation) in order to be able to respond to ongoing and anticipated changes (such as, increasing need for software-related capabilities in robotics products) while maintaining optimal use of resources. COMAU and KUKA responded differently to their environment – KUKA demonstrated the expected change in the exploitation-exploration mix but COMAU did not commit to any significant rebalancing. Expected tradeoffs between local and distant search (or the exploitation vs. exploration dynamic) occurred only in limited periods; more significant was the parallel increases in both search scope and COMAU's local search tendencies,[12] and the continuing level of self-citations compared to the dynamic search traits in KUKA's knowledge base throughout the period studied. These observations provide strong support for the notion of exploration-exploitation dynamics being orthogonal rather than contrasting activities within a trade-off which are available to resource-rich organizations.

There is a level of stability across all our measures. Apart from the notable stability in technological diversity, there are comparable (albeit limited) consistencies in the other measures (i.e. relatedness of developed core competencies, stability of search combinations). Collectively, these confirm the routinized and cumulative nature of the evolutionary firm. Similar to the observations in Ahuja and Katila (2004) regarding chemical firms, the case robotics firms

[12] This shift is seemingly driven by COMAU's acquisition of other companies cited in its previously patent applications (i.e. Renault Automation, Sciaky Industries)

exhibited a strong tendency for maintaining established knowledge-acquiring activities across time. In line again with Ahuja Katila's (2004) findings, the changes observed in these enterprises were incremental but dynamic.

However, our qualitative and quantitative exploration of the innovative behavior of two leading robotics firms underscores the effect of context specificities (and how they produce heterogeneous firm responses). COMAU maintained a conservative approach with a significant refocusing on core activities during the mid-2000s followed by attention to economic performance while KUKA showed a stronger inclination for technological diversification. COMAU's conservatism might be explained by its extensive links to the FIAT Group (now FCA Group); its innovative behavior may have been influenced significantly by its parent company's corporate strategy i.e. cost cutting and survival in the late 1990s early 2000s, and modernization of Chrysler's plants in the FCA Group during the late 2000s and early 2010s. News reports in the most recent years suggest that the FCA Group is following a strategy of listing and selling some of its most valuable controlled companies (see the listing of Ferrari and sale of Magneti Marelli) to raise capital – it might be that COMAU will be the next to go.[13] If so, pursuing a risky diversification strategy could have negative impacts on COMAU's profitability making it less attractive to future investors. The firm's conservative behavior could be the result of financial targets rather than strategic technological decisions. We acknowledge that this interpretation might be affected by our reduced patent sample for COMAU since part of its patenting output could have been concentrated in the FCA Group's designated R&D laboratories (cursory investigation reveals that Centro Ricerche has had substantial patenting output in robotic related areas in recent years), especially after the 2007 consolidation of FIAT's research efforts in its two main labs. Thus, there might be sample bias if FIAT/FCA made the strategic decision to retain in the mother company the most strategically relevant patents related to technological diversification.

In contrast, KUKA after its restructuring, refocused on diversifying its robotics production into more advanced robotics fields. KUKA leveraged its expertise and expanded into non-traditional applications such as interactive robots and medical robots, via various acquisitions in the Reis

[13] Such strategy can result in a reduction of the debt of FCA but at the same time in a loss of control of most valuable competences in the area of digital manufacturing. However, the willingness of the FCA Group to sell COMAU may be attributable to limited R&D activity already being carried out in the company.

Group and Swisslog Holding AG. This allowed KUKA to gain familiarity in these areas without a lengthy capability-building process. In January 2017, the Midea Group bought 74.55% of the voting stocks of KUKA for EURO 4.5 Billion; this was a strategic investment for the Chinese group founded on the very high potential growth of the Chinese robotics market.

Another aspect of the restructuring processes was the quite abrupt shifts in the firms' behavior which points to the stronger impact of internal reorganization relative to any environmental stimuli. Their internal restructuring brought about the most sweeping organizational changes. However, we are unable to determine the exact relationship between these activities. An internal reorganization can affect all firm aspects in quite dramatic ways. For instance, changes to employee counts and the firm's activities can contribute to shifts in its knowledge-related heuristics. It is possible also, that the routinized behavior within the organization before the mid-2000s was based more on success than on failure, causing the firm inadvertently to focus on short-run objectives and neglect long-run adaptability (Levinthal & March, 1993). Attempts could be made to disentangle and isolate the effects of intra-firm change (in particular, restructuring programs and M&A deals) on modifying the enterprises' overall innovative behavior. There is a growing strand of work that explores the particular effects of M&A activities in innovative behavior (among others, Cloodt, et. al., 2006), with an increasing number of studies focused particularly on M&A strategies in relation to pharmaceutical and life sciences companies (see among others, Prabhu, et. al., 2005; Mittra, 2007). Firms facing radical technological changes use acquisition as a strategy to acquire new sets of competencies rapidly (see Google's acquisition strategy). It might also be possible to determine the effect of the firms' position within its supply chain (or within the broader global value chain). Being part of a large network of affiliated companies (i.e. COMAU) vs. being an individual 'retailer' of capital goods (i.e. KUKA) may have affected these firms' innovative heuristics. Future research could extend the analyses in several directions. First, research could attempt to identify explicit and quantifiable relationships among the selected set of measures on innovative behavior and firms' competitive advantage and performance.

In terms of our initial research questions, can we say that there are historical antecedents supporting the expectation that robotics companies generally are able to radically innovate? Can they be expected to revolutionize manufacturing? Are the latest attention-grabbing robots in the media representative of where the industry is now or will be in ten years' time? Overall, our finds seem to indicate that robotics companies are not the harbingers of a revolutionary future they often are seen as; they tend to prefer continuity and are likely to remain in familiar territory. While these enterprises are attentive to current developments in their external environment, they are highly selective about which to assimilate into their established operations. High-technology firms respond conservatively to external stimuli; internal shifts bring about very noticeable and abrupt changes to their innovative propensities. More broadly, they add to the many examples in the history of technology suggesting the lengthy process involved and organizational boundedness of technological progress. Going from the moment of the first appearance of a new technology –e.g. smart robots- to mass production requires major accumulation of new technological knowledge by producing firms and significant organizational changes in adopting firms. In some cases, incumbent firms are unable to adapt (see the case of Kodak and digital photography), in others acquisition of small innovative companies allows the dominant player to survive (see the evolution of the pharmaceutical industry and the emergence of biotechnology).

These notions of the firm have important business and policy implications. The accounting focus in industry peers' actions and development during benchmarking exercises may be limited for providing the firm with the necessary perspectives for sustained growth. Contemporaries may be similarly shortsighted in their anticipation of external threats and may be conservative in their search for opportunities. Setting courses of action based on existing paradigms can inevitably link the individual firm's fate to that of the broader industry.

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Appendix A. **Documentation on methodology**

The *technological diversification* measure is calculated by comparing the firms' 4-digit level IPC subclasses-based diversification indices. An index is derived from a set of unique IPC subclasses constructed for each stock-year from 1991 to 2015. This approach and specification is based on the recommendations of earlier studies (van Zeebroeck, et.al., 2006; Caviggioli, 2016).

Following Quintana-Garcia & Benavides-Velasco (2007), the *technological diversification* measure is specified as follows

$$Technological\ diversification: 1 - HHI = 1 - \sum_i p_i^2$$

where p_i denotes the proportion of patents in technical field i. The index is equal to zero when a firm researches only in a singular technology and approximates unity when the enterprise spreads its research activities over a wide technological base (Quintana-Garcia & Benavides-Velasco, 2007). Consistent with Quintana-Garcia & Benavides-Velasco's (2007) use, patents assigned to multiple technical fields have been treated as different applications.

The *technological competence* profiling is conducted via the Patel & Pavitt's (1997) technological profile matrix, which relies on a combination of Revealed Technological Advantage (RTA) and patent share (PS) to map out firms' technological capabilities. RTA is calculated as follows:

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

wherein P_{ij} is the number of patents of firm i that belongs to IPC class j applied with the EPO. Because of data constraints, we had to rely on the OECD data on all patent applications to the EPO from 1987 to 2014. Meanwhile, PS is calculated as the share of a particular IPC subclass in the firm's total IPC subclasses for a particular stock-year. Table A1 provides the matrix's classifications and their respective RTA & PS conditions.

Table A1. Patel & Pavitt's (1997) classification of technological competencies,

Classification	RTA condition	PS condition
Core technology	RTA > 2.0	PS > 3.0 %
Background technology	RTA < 2.0	PS > 3.0 %
Marginal	RTA < 2.0	PS < 3.0 %
Niche	RTA > 2.0	PS < 3.0 %

The competencies are defined as follows: core as the firm's distinctive technical competencies, niche as those that are distinctive but are relatively small technological fields, background that are competencies wherein the firm allots significant resources but is unable to achieve a relatively high advantage because of the field's size, and marginal in which the firm neither allocates sizeable resources nor achieves distinct advantages (Patel & Pavitt, 1997).

The *local-distant search* measure is studied through a comparative analysis of Katila & Ahuja's (2002) search scope measure and Rosenkopf & Nerkar's (2001) self-citation measure. Both measures first are calculated based on the unique patent citations (and their corresponding assignees) made for each *stock-year*; from that dataset, a firm citation stock was calculated as:

$$firm\ citation\ stock_t = firm\ unique\ patent\ citations_t + firm\ unique\ patent\ citations_{t-1} + \cdots + firm\ unique\ patent\ citations_{t-4}$$

The search scope is calculated as:

$$Scope_{it} = \frac{new\ citations_{it}}{total\ citations_{it}}$$

wherein new citations are citations that were made in $firm\ search\ scope\ stock_t$ but not in $firm\ search\ scope\ stock_{t-1}$ and $total\ citations_t$ are $firm\ citation\ stock_t$.

The self-citation measure is calculated as:

$$Self - citation_{it} = \frac{self - citations_{it}}{total\ citations_{it}}$$

wherein self-citations are citations of the firm's, its subsidiaries', and affiliated organizations' previous patents and $total\ citations_{t-1}$ are $firm\ citation\ stock_t$.

Appendix B. COMAU SpA (Italian operations) financial highlights 2008 - 2015, in thousands EUR

	2008	2009	2010	2011	2012	2013	2014	2015	Average
Current assets	527,805	324,025	249,547	388,778	432,369	591,894	896,354	1,083,279	561,756
Total assets (TA)	718,537	519,776	450,467	517,310	582,206	752,832	1,037,334	1,196,890	721,919
Non-current liabilities	87,758	91,789	67,977	85,662	69,855	73,251	60,778	58,886	74,494
Current liabilities	544,639	347,618	285,085	358,933	430,218	589,650	828,571	967,504	544,027
Total liabilities (TL)	632,397	439,407	353,062	444,595	500,073	662,901	889,349	1,026,390	618,522
Operating revenue	446,707	200,053	234,403	344,392	343,835	359,971	464,452	486,232	360,006
Period P/L (Net income)	-15,805	-45,771	-22,964	-144,691	9,418	7,798	58,054	22,514	-16,431
No. of employees	1,626	1,217	1,070	1,042	1,112	1,187	1,277	1,309	1,230
Current (working capital) ratio	0.97	0.93	0.88	1.08	1.00	1.00	1.08	1.12	1.01
TL/TA ratio	0.88	0.85	0.78	0.86	0.86	0.88	0.86	0.86	0.85

Source: Amadeus database (2018)