Scientometrics (2016) 107:819–837
DOI 10.1007/s11192-016-1862-0

Disentangling the automotive technology structure: a patent co-citation analysis

Manuel Castriotta[1] · **Maria Chiara Di Guardo**[1]

Received: 20 July 2015 / Published online: 30 January 2016

Abstract While most technological positioning studies were traditionally addressed by comparing firms technological patents classes and portfolios, only a few of them adopted science mapping patent co-citation techniques and none of these seeks to understand the impact of collective cognition on the technology structure of an entire industry. What is the firms technological positioning landscape within an high collective cognition sector? What is the groups technological positioning evolution? How do technology structures shift according to different economic scenarios? Through a strategic lens we contribute to technology strategy literatures by proposing an invention behavior map of automotive actors at a firm, groups and industry level. From Derwent Innovation Index, about 581,000 patents, 1,309,356 citations and 1,287,594 co-citations relationships between (a) the main 49 firms assignees of 1991–2013 and (b) the main 28 or 34 groups assignees by considering three timespan 1991–1997, 1998–2004, 2005–2013, were collected. Results: (1) most of the companies are located close together, depicting the sector technology structure as highly dense; (2) the market leaders do not coincide with technology production leaders and not necessarily occupy central technological positions; (3) the automotive groups considerably varies in the three timespan in terms of position and composition; (4) the market leaders groups occupy technological remoteness positions during economic growth timespan; (5) the sector technology structure is highly dense during growth, strongly scattered and lacking of technologically center positioned actors after economic decline. Finally, strategic implications supporting central locating or suburb R&D positioning planning and M&As recombinational partners decision making are discussed.

Keywords Patent co-citation analysis · Patent strategy · Technology structure · Technological positioning · Collective cognition

✉ Manuel Castriotta
manuelcastriotta@gmail.com; manuel.castriotta@unica.it

Maria Chiara Di Guardo
diguardo@unica.it

[1] University of Cagliari, Viale Sant'Ignazio, 73, 09123 Cagliari, Italy

Introduction

Patents have many advantages for a successful business. By creating patents, firms can build entry barriers, earn profits through royalties, and increase brand awareness, ultimately shaping their own technological positioning. The traditional line of research in this field has focused on analysis at the firm level, and the description of external context in competitive terms has typically assumed an atomistic notion of firms' evaluations of patent opportunities. However, the empirical literature on technological regimes argues that firms within an industry behave in correlated ways because they share sources of information and technology (suppliers, universities, other industries), and perceive similar opportunities for innovation (Nadkarni and Narayanan 2007; Narayanan et al. 2010). The existence of a collective cognition shared by firms within a sector can also influence how inventions arise, how quickly and completely they diffuse, and the technology structure that has characterized some sectors.

Yet, while collective cognition has received increased attention in the broader field of organizational theory (Johnson and Hoopes 2003; Nadkarni and Narayanan 2007; Narayanan et al. 2010), research on patent strategies and innovation has been largely silent about the cognition's role (Kaplan 2011, 2012; Kaplan and Tripsas 2003, 2008). Moreover, although extant literature notes that firm behavior is clearly influenced by collective cognition within a sector, and researchers have emphasized the existence of a different degree of homogeneity/heterogeneity across sectors (Abrahamson and Hambrick 1997), little is known about how this industry-level discretion can affect the technology structure of an entire industry.

In this paper, we study the firms' technological positioning landscape within a high collective cognition sector, and in particular we look at the automotive sector from 1991 to 2013 identifying the dynamic evolution of patent paths among the principal actors. In so doing, we propose a large patent co-citation cartography of the automotive industry, which represents the cognitive process underpinning the development of technological positioning strategies.

We chose the automotive sector for several reasons: first, the ability of firms to innovate is crucial to commanding a competitive advantage in this industry (Nohria and Garcia-Pont 1991); second, all relevant players in this industry must routinely patent their innovations; third, the automotive market is characterized by high entry barriers able to isolate new entrants' and incumbents' dynamic noise; fourth, the automotive industry is characterized by a group of companies that have historically competed in the market to gain competitive advantages and for this reason they have had time to meet and increase maturity of their shared beliefs or collective cognitions (Abrahamson and Hambrick 1997); finally, the emergence of a vast network of joint ventures, strategic alliances, and mergers and acquisitions among heterogeneous organizations has been one of the key distinguishing traits in the recent evolution of this industry (Zapata and Nieuwenhuis 2010; Wells and Nieuwenhuis 2012; Schulze et al. 2014).

In order to understand the phenomenon at stake, we use patent co-citation analysis. Previously, the most common method of patent analysis was to count patent documents and compare how many of them had been assigned to each entity (Lai and Wu 2005). However, current research goes beyond the mere identification of trends in patent statistics and attempts to capture several dimensions of technology assessment and foresight using novel and dynamic techniques based on science mapping (Youtie et al. 2008; Porter and Rafols 2009; Porter and Youtie 2009; Rafols et al. 2010; Kay et al. 2014). In this line of research, we analyze the evolution of the technology structure in the automotive sector by utilizing bibliometric information such as patent co-citations (Lai and Wu 2005; Wang et al. 2011). This approach displays a larger picture of the overall knowledge structure and the firms' technology positioning, thereby shedding light on the patterns of patent strategies within an industry. Therefore, we draw from longitudinal patent bibliometrics and patent co-citation quantitative approaches for the period from 1991 to 2013.

From the Derwent Innovation Index, about 581,000 patents, 1,309,356 citations, and 1,287,594 co-citations relationships between: (a) the main 49 firms' assignees from 1991 to 2013; and (b) the main 28 or 34 groups' assignees by considering three timespans (1991–1997; 1998–2004; 2005–2013) were collected. Multidimensional scaling and cluster analysis techniques are employed to detect the cognition homogeneity level and to provide an overview of the groups' technology composition and companies' innovation strategy trends. Finally, explorative findings are discussed below with suggestions about how they might be translated into managerial implications.

This study adds to the literature in multiple ways. First, it contributes to the patent literature showing the evolutionary patterns of patent strategies inside a specific industry using patent co-citation analysis. Second, it contributes to innovation literature by enhancing our understanding of how technological firms and group positioning evolve. Third, it also contributes to the still-inadequate understanding of collective cognition drivers of patent strategies of an entire industry.

The paper is organized as follows. In section two we present our theoretical background; in section three, we describe the patent co-citation methodologies employed; in section four, we present our results and provide a graphical representation of firms' and groups' proximities performed by multidimensional scaling (MDS) and cluster analysis; in section five, we discuss the results; and finally we offer several conclusions and recommend avenues for future research.

Theoretical background

Collective cognition

The collective cognition is not merely the sum of individual cognition but rather the high level of cognitive "congruency" between groups of individuals, companies, or organizations in terms of data processing or mental representations (Hodgkinson and Healey 2008).

The extant literature has shaped this concept in different ways, either through using a strategic approach (Nohria and Garcia-Pont 1991; Kaplan 2011, 2012; Kaplan and Tripsas 2003, 2008) or focusing on managerial cognition (Abrahamson and Hambrick 1997; Nadkarni and Narayanan 2007; Narayanan et al. 2010), or even examining the broader cognitive dynamics of the group mind (Hodgkinson and Healey 2008). From the point of view of semantic, the construct of collective cognition is often associated with group learning, group memory, and distributed cognition (Islam 2015). Prior literature provides a plethora of definitions of collective cognition. West (2007) defined it as "the content of combination of individual perspectives and the structural characteristics of that combination." Gibson (2001) defined it as a group mind that resides "in the interrelation between the activities of group members."

However, the primary objective of all these studies was to respond to conceptual issues raised by scholars of different fields (sociology, economics, philosophy, etc.) in order to provide a convincing explanation useful to predict individual reactions or behavior connected to group belonging at the firm and industry levels. In this regard, outstanding organizational theories such as population ecology and institutional theory attempted to better understand these cognitive dynamics (Cyert and March 1963; Hannan and Freeman 1977; Di Maggio and Powell 1983).

From a strategic point of view, Nohria and Garcia-Pont (1991) make a first attempt at investigating the industry structure in terms of strategic groups of firms with similar features and strategic capabilities. They attempted to provide insights about the relationship between strategic choices, tacit knowledge of the business groups, and firm strategic behavior. Consequently other researchers have brought attention to the more strictly cognitive research providing two approaches: computational and interpretative mental representations. In the first case, starting from the concept of the Touring collective intelligence machine, the authors attempted to split the cognitive mechanisms requiring attention to processes such as perception, memory, data processing, problem solving, and rational decision-making. In this regard, Hodgkinson and Healey (2008) synthesized four phases of collective cognition: accumulation (i.e., knowledge perceiving, filtering, and storing), interaction (i.e., information retrieving, exchanging, and structuring), examination (i.e., idea negotiating, interpreting, and evaluating), and accommodation (i.e., idea integrating, deciding, and acting). The second, exemplified by Weick's work, emphasizes the upstream processes of sense making used by individuals and groups to exploit schemas of meaning from ambiguity in the social construction of organizational realities (Hodgkinson and Healey 2008; Kaplan 2011, 2012; Kaplan and Tripsas 2003, 2008). In this view the authors believe the focal element of imaginative representations and mental interpretations. Both approaches seek to shift the individual dynamics in the group. In this regard, a number of studies raise the question of whether the collective cognition can be necessarily understood in a literal or metaphorical way or if cognition is possible only within the mind of the individual or externally through the relationships between groups (Islam 2015).

Following the interpretative approach of collective cognition, we propose a large patent co-citation cartography of the automotive industry, which represents the cognitive process underpinning the development of technological positioning strategies.

Patent analysis

Patents, defined as contracts whereby an invention is disclosed in exchange for potential economic exploitation by an inventor or assignee, are fundamental assets able to determine companies' competitive advantages (Lai and Wu 2005). Academic scholars have used patents as a measure of technological innovation outputs in relation to productivity, economic performance, or profits (Seol et al. 2011).

Patent analysis is a method used to transform patent data into useful information about a product's developmental status, the market-competition landscape, competitive intelligence, technology structures and positioning, commercialization strategies, R&D planning, and the management of intellectual property (Archibugi and Pianta 1996).

Furthermore, patent analysis is often used to analyze the competition and trends in technological changes in national and international context, to estimate technological strengths and weaknesses of competitors, and to evaluate the potential of foreign markets. Patent analysis is also a valuable approach that uses patent data to derive information about a particular industry or technology used in forecasting (Narin 1994; Kim et al. 2008). Jaffe (1986) used patent analysis to characterize the technological position of US firms, while

Cheung and Ping (2004) used it to investigate the evolution of the technological capabilities of Korean semiconductor firms.

It can be used to study technologies (Brockhoff 1991) focusing on single patents or classes of patents but also on firms' patent strategies through the patent portfolio analysis (Ernst 2003), defined as a set of patents that are related to a specific subject or technology. Combining approaches, analysts can obtain a patent landscape (Brockhoff et al. 1999).

There are many international classification systems that discriminate in terms of numbers, structures, borders, definitions, and denominations of classes. This strong element of heterogeneity associated with the difficulty of standardization and the consequent existence of significant elements of subjectivity increases the potential for assessment inaccuracies. From a technological point of view, technology structure analysis usually generates significant discrepancies in broad patent analysis (Abraham and Moitra 2001).

Bibliometrics and patent citation analysis

Patent citation analysis is an academic set of bibliometric methods directly derived from methodology that seeks to link patents in the same way that science references link papers. Papers and patents are both research instruments that adopt citation-count measurement systems (Narin 1994). Moreover, in bibliometrics, the use of a citation approach for the assessment of similarity for the classification of documents is a mature methodology, and for this reason, it is feasible to apply the citation analysis of bibliometrics to patent analysis (Lai and Wu 2005; Wang et al. 2011). Patent citation analysis deals with the count of citations of a patent in subsequent patent or non-patent literature. Citations are reliable indicators of the importance and influence of the prior art to subsequent inventions, and citation means adoption. Highly cited patents include important technological advance.

Therefore, the count of citations is an indicator of the technological impact of the patented invention. Patent citation analysis has been used to evaluate research performance, and economic studies suggest that patent citation counts correlate to economic value (Zhao and Guan 2013). Interesting studies have adopted patent analysis in order to demonstrate that new knowledge comes from combinations of previous knowledge in terms of local and far distances and results (Lai and Wu 2005; Wang et al. 2011). Patent citation analysis has been used as a measure of technological quality and influence and to study the diffusion of technological information. Patent citations are also used to construct technological indicators.

Patent citation analysis's advanced techniques allow analysts to assess not only the quality and impact of cited material but also the linkages among cited and citing countries, companies, and scientific and technological areas (Zhao and Guan 2013). It is also a useful competitive intelligence tool. Narin (1994) have demonstrated how to use patent citation counts to identify technical complementarities and competition among patenting firms by adopting techniques of competitor assessments like citing and cited patents, citation impact, and technology profiles and maps. In this direction, recent studies recognize the role of science maps as useful means able to capture the multifaceted features of patent applications in terms of technological advancements and positioning. This technique has been first validated in bibliometrics and then adopted for investigating convergence and degree of interdisciplinary in patent landscape research (Youtie et al. 2008; Porter and Rafols 2009; Porter and Youtie 2009; Rafols et al. 2010; Kay et al. 2014).

Patent co-citation analysis

Co-citation analysis is a measure of the frequency of how many times A and B units are co-cited by third units such as papers, authors, institutions, and in our study patents, inventors, or assignees (Lai and Wu 2005; Wang et al. 2011; Castriotta and Di Guardo 2015). The assumption of co-citation analysis is that documents that are frequently cited together cover closely related subject matter (Small 1973; Narin 1994). In this vein, the co-cited frequency of patents can be used to assess the similarities or relatedness and to post evaluation and less-subjective unobtrusive patent maps and classification systems (Lai and Wu 2005). Co-citation analysis (Small 1973) is an advanced bibliometrics method specular to bibliographic coupling one. The first focuses on cited documents' potential infinite measures, while the latter is limited to citing references. In bibliometrics, it is used to assess document similarities in order to analyze the intellectual structure of science studies and identify cluster specialties and sub-fields (Di Stefano et al. 2012). In patent analysis, the co-citation approach has been used to study the structure of knowledge in various specific fields, such as nanotechnology (Kostoff et al. 2006), engineering (Murray 2002) and topology (Wallace et al. 2009). Lai and Wu (2005) adopted co-citation as a tool capable of increasing the objectivity of the patent classification system and to assist patent managers to better understand the basic patents for a specific industry and the relationships and evolution of technology categories. Although these research efforts have focused mainly on single patent or technology classes, there is a gap in the level of co-citation analysis with the aim to show the technology structure of an entire industry over time through the development of cognition and its relation to economic and market trends. For these reasons, the main goal of this line of research is to shift the focus to assignees in order to understand in detail the development of a specific industry sector.

Methodology

Sample and unit of analysis selection

Our analysis, following the bibliometric co-citation and patent co-citation methods prescriptions (McCain 1990; Nerur et al. 2008; Di Guardo and Harrigan 2012; Wang et al. 2011) and in order to correctly select the unit of analysis started by tracing the history of most relevant M&As and alliances automotive industry milestones. This allow us to consequently identify in Derwent database the standard and non standard assignees codes for the overall and intermediate periods and correctly formulate compound Derwent Innovation Index and Derwent World Patent Index search queries (Wang et al. 2011). A retrieving of assignees patent bibliometrics and assignees patent citation counts and finally co-citation frequencies is followed. Operationally, the compilation of the raw co-citation matrix and its conversion to correlation matrix allow us to run multivariate analysis and consequently interpreting the findings. In the case of academic bibliometric studies, the unit of analysis may consist of scientific articles, authors and institutions (Small 1973). Symmetrically in the study of the citations behavior in the patent analysis, the unit of analysis can be identified by single patents, inventors, institutions or assignees (Lai and Wu 2005). Our research aims to show the technological positioning and similarities between the leading automotive companies and the entire sector technology structure and for these reasons we adopted assignees and as unit of research.

The underlying assumptions of this choice are that: (1) the greater the number of citations received by a single assignee or assignee-code the greater is its scientific impact or quality; (2) the greater the number of citations received the entire patent portfolio, the greater is the impact of technology and research and development of automotive assignees; (3) Finally, the greater the number of simultaneous citations or co-citations between assignees, the higher is the level of similarity and proximity perceived by citing world assignees.

Basically if two firms are cited together by third citing assignees, we assume that they have a strong technological relationship which should be seen in the technology structure map (multi dimensional scaling) and in the other multivariate analysis. In this study, we explored the Derwent Innovation Database with the two indices Derwent Innovations Index (DII) and Derwent World Patent Index (DWPI) databases, representing the most complete and comprehensive patent information source in the world. Active since 1963, it fully covers the last 50 years of patent history and comprises more than 14 million patents worldwide. It continuously monitors more than 40 international and national authorities involved in the management and licensing of the world patent system. It offers the possibility to search for patents based on international classifications as well as having its own patent classification systems. Furthermore, it offers a range of additional services that allow not only the patent, inventors, and assignees citation analyses but also fully instrumental tools to retrieve cited and citing actors' statistics. In this regard, we adopted assignee traditional and non-traditional Derwent codes to search queries to detect patent bibliometrics and citations statistics. Starting from the OICA 2013 report ranking, we selected the top 80 global companies in the automotive industry of manufacturers based on the number of commercial, passenger, and industrial vehicles produced. We examined the companies' websites and identified the number of brands for each company and its automotive groups. In the Derwent database, we checked individually for brands, single companies and groups, and the number of patents of the application date for the period 1991–2013. In this way, we divided the commercial brands by independent enterprises capable of producing technology. Then we looked back across the brands' histories, alliances, and M&As that occurred in the years between 1991 and 2013. Operationally, the major companies have a unique standard code "C". The lesser known or smaller companies and those of the Chinese market are identified by non-standard codes that have been precisely identified through a manual assignee search. For accuracy, 37 companies of 60 have unique four-digit character identifications, while for the remaining 23 it was necessary to formulate ad hoc search queries. In addition, in order to avoid the traditional limitations due to strategic and formal changes in companies and group structures, Derwent provides a comprehensive data set of joint ventures drawn up within industries in the period considered. Unfortunately, from the operational point of view, that research is not yet coded or currently linearly provided by Derwent, and for this reason, we have followed the correct search strategy proposed by Wang et al. (2011). In the research, we took into consideration 18 joint ventures formalized during the period among 21 companies. Then, we launched an investigation of patent bibliometrics and identified the number of citations of the top 60 car manufacturers. At this point, we launched the number of citation queries and identified and measured the impact of the patent portfolios of businesses. Finally, we analyzed the significant differences between car production, technology production, and the impact of the latter on the automotive industry technology structure. For the period 1991–2013, we chose to analyze individual companies found without taking into account the group to which they belonged. In this way, we were able to verify the contribution of each individual firm on patent portfolios in terms of group-similarity level. Then we divided the whole period into three sub-periods of 7 years (1991–1997, 1998–2004, and 2005–2013), considered suitable to fill the well-known methodological bias due to the fact that the process of patent granting gives operating results usually after 3 years. The final period is 1 year longer because citations and patent applications are maturing slower in recent years. Furthermore, in the hope of exploring the potential effects of the crisis in the technological positioning of groups, we considered these in conjunction with the Asian crisis of 1997–98 and just before the start of the crisis of 2007–2008. Moreover, we took into account the M&A histories that showed that in these three periods, the most influential automotive group changes were concentrated. In summary, we propose a large patent co-citation cartography of automotive industry.

Patent data and multivariate analysis

By screening the Derwent Innovation database and according to the above search criteria, we selected data from about 581,000 patents, 1,309,356 citations and 1,287,594 co-citations of 60 automotive assignees in the period 1991–2013. Given our interest in defining the hard core of the technology firm positioning, we selected only the most cited patent portfolios (Acedo et al. 2006; Wang et al. 2011). Coherent with other bibliometric studies (Culnan 1986; Rowlands 1999) and patent co-citations (Wang et al. 2011), the selection was set at 100 citations for patents issued between 1991 and 2009, 80 citations for patents applied to 2010. The filter has highlighted the 60 most cited companies on which it was carried out and retrieve the co-citation matrix. Finally firms whose columns in the table of co occurrence had a higher number of two-thirds of equal zero were eliminated. For the same reasons and following the same method but applied not to individual companies but to groups in the period 1991–1997 were selected 28 variables, in 1998–2004 another 28, and in the last 34. In order to standardize the data and avoid possible scale effects, prior to the analysis we converted the raw co-citation matrix into a correlation matrix, using SPSS Version 20 to calculate Pearson's correlation coefficient for each cell of the matrix (Rowlands 1999).

In recent years, the Pearson's correlation matrix has animated a considerable debate in the academic arena, generating two opposing points (Mêgnigbêto 2013). On one hand, some scholars consider it as a problematic tool to assessing similarity between authors (Ahlgren et al. 2003; Bensman 2004; Egghe and Leydesdorff 2009; Leydesdorff and Vaughan 2006; Van Eck and Waltman 2008, 2009), while on the other hand, and mainly in the light of the methodological positions of White 2003, many studies rely on the r performance and still use it for the co-citation analysis (Ravikumar et al. 2015; Shiau and Dwivedi 2013; Hsiao and Yang 2011; Shiau et al. 2015; Cho 2014; Yan et al. 2015; Sugimoto et al. 2008; Jeong et al. 2014; Hu et al. 2010). Within this context, our aim was first, to provide rigorous results while simultaneously avoid methodological experimentation, and second, to adopt the more coherent choices with the research question. For these reasons and because traditional methodologies seemed more appropriate in light of the research focus on the overall automotive technology structure analysis, we adopted the White approach. Nonetheless and in a complementary methodological point of view with respect to other studies, we emphasize the need to continue investigating the field of patent co-citation analysis through different similarity measures and multivariate analysis.

Once the correlation matrix was obtained, drawing on similar studies (Culnan 1986), we proceeded to apply two multivariate statistical techniques to the correlation matrix. First of all, non-metric Multidimensional Scaling (MDS) was employed, allowing us to mapping the relationships between technological positioning of assignees. With this map you can have an indirect measure of similarity between the companies and groups and consequently the entire sector technology structure. Furthermore, the evolution of the assignees relationships may be discerned by examining changes in the structure of such maps over time. Secondly, we applied a Cluster analysis, which groups the papers in terms of similarity thus providing an indication on the most relevant patent positioning subfields. Cluster Analysis can be used to determine which companies and groups are jointly related and therefore share a common elements. It does so by producing a number of “clusters”, each of which captures a common element of the documents that are grouped together. Additionally, it produces numerical indicators of the relevance of the clusters thus telling us something about the relative importance of these underlying elements. Clusters were extracted by hierarchical Ward method (Rowlands 1999).

Mergers and acquisitions (M&As) and joint ventures (JVs) group histories

Players in the automotive sector are characterized by a strong propensity for the development of strategic alliances, mergers and acquisitions, and joint ventures (Nohria and Garcia-Pont 1991). The search for patenting/innovation and commercial bonds increases business potentials by making more efficient technology transfer processes, competition capabilities, information-management skills, knowledge, and trust. The nature of these relationships also deeply affects the individual and collective cognition of the industry and the groups to which companies belong (Kaplan and Tripsas 2008). In this light, a historical analysis of the most relevant and established formal relations that have occurred since 1991 in the automotive industry follows. In this 22-year period, the shape and properties of automotive manufacturers have deeply changed. Currently, the Toyota group comprises Hino Motors and Daihatsu (since 1998). Volkswagen owns Audi, Skoda, SEAT, Bentley, Lamborghini, and since 1998, Bugatti, Scania (2011), and MAN (2011), and after a long series of disputes, even Porsche (2012). Hyundai and Kia jointly formed the main South Korean automotive group in 1998. Ford, until the crisis in 2007, has owned a series of relevant automobile manufacturers such as Jaguar and Land Rover, which currently belong to the Indian group Tata, and Volvo from 1999 until 2009, which is currently owned by Chinese carmaker Geely, and finally Aston Martin, which currently is owned independently. Honda, Suzuki, PSA, Mazda, Mitsubishi, Fuji Subaru, Isuzu, and the Indian company Mahindra & Mahindra have maintained their independence in the time period considered. The latter entered into a major joint venture with the American company Navistar between 2005 and 2013. Nissan and Renault signed an important strategic alliance in 1999, and the latter acquired Dacia Motors in 1998. Chrysler, independent until 1997 along with Jeep and Dodge, was in a major merger with Daimler from 1998 to 2007, and then, because of the crisis of 2008, began a journey that has led today to its merger with the Italian group Fiat. Daimler AG with the exception of the temporary bond with Chrysler has consistently maintained its integrity, as has the Fiat group. The latter is composed of a number of prestigious brands such as Ferrari, Maserati, Alfa Romeo, and Lancia. BMW now owns the prestigious Rolls Royce and between 1995 and 2006 also owned the Land Rover manufacturer. Since 1999, the Volvo group has exclusively produced heavy commercial vehicles and has acquired Renault trucks. Finally, the main Chinese enterprises are characterized by a large number of joint ventures with Japanese, European, and American groups. The main groups are Saic with Saic-Iveco, Saic Volkswagen, and Saic-GM-Wuling. Dongfeng Motor cooperates with PSA, Honda, and Nissan, and Kia Changan maintains relations with Suzuki, Mazda, Ford and PSA. Baic formally participates with Beijing Hyundai, Beijing Benz Daimler AG, and Beijing Foton Daimler in joint ventures.

The FAW Motors group is engaged in relationships with Toyota and Volkswagen, BMW with Brilliance Automotive, and finally the GAC group with Fiat, Toyota, Mitsubishi, Honda, and Isuzu. Gaig (Guangzhou Automobile Industry Group) has a commercial relationship with Toyota and Honda, while Great Wall and Lifan Motors have no current formal collaborations with other international groups.

Results

Patent bibliometrics

Patent bibliometrics highlights substantial differences in the world's car production rankings. Essentially, the most efficient technology manufacturers do not coincide with the major manufacturing sellers. In this vein and considering JVs, the analysis shows clearly what the commercial relationships are and the alliances, rather than those with goals of a technological nature. Car manufacturers who mainly patented in the reference period are Toyota, Hyundai, and Honda, with 120,680, 87,428, and 55,801 patents respectively. These were followed by Nissan, Daimler, and General Motors, and finally Ford, Mazda, and Volkswagen closed the top 10. Geely is the first manufacturer of Chinese technology, followed by Chery and Dongfeng. Under the top 20 patent ranking, are positioned Aston Martin, Lamborghini, Alfa Romeo, Bugatti, and Maserati. Japanese and Western companies hold supremacy in technological leadership. JVs with Chinese manufacturers have a mainly commercial nature. The data show clearly that only in recent years have the Chinese experienced patent production. By consolidating wherever possible up to 2012, the ranking of the groups did not change significantly. Toyota, Hyundai, and Honda remain firmly in the top three, while Volkswagen moved from tenth to sixth place and Fiat from 26th to 22nd. The analysis of patent citations generated by companies highlights the impact not only of the patent portfolio but also of patent strategies. The measurement of total citations in the period 1991–2013 shows that Toyota, Nissan, and Honda occupy the first three places respectively with 196,478, 139,144, and 138,975 citations. They are followed by Daimler AG, General Motors, Ford, and Chrysler. Finally, Volkswagen, BMW, and Mazda complete the top 10. The citation impact of Chinese groups is absolutely reduced and proof of this is the Geely group in 39th place and of the latest 5 posts occupied by Chinese companies. The analysis of the impact of patents on the basis of quotations significantly changes the ranking to show that the number of patents does not always generate greater impact and also that not all patent strategies comply with the principle of parsimony but also have the objective of protection. In this ranking for the group, Paccar, Navistar, and Ford occupy the top three spots followed by Fiat, General Motors, Porsche, and MAN. Particularly disappointing results in terms of the impact of Chinese enterprises were most of Daewoo Motor, Mahindra, Scania, and Daihatsu.

The automotive technology structure

The analysis of co-citations highlights the technological positioning of the 49 major automotive companies in the global market in the period 1991–2013, 28 of the main groups in the periods 1991–1997 and 1998–2004, and finally the 34 major groups between 2005 and 2013. During the full period, the unit of analysis is the single automaker, while in the three time spans, it is the automotive group through the extraction of aggregate data.

The analysis of the complete map and the trends and changes in technology portfolios in the three time spans, considering the M&A histories and joint ventures, are discussed below through the results of multidimensional scaling and cluster analysis.

On the left, the map shows an area of high concentration and high technological similarities, while on the right, the distances among firms increase (Fig. 1). In this scenario, cluster analysis clearly highlights four groups. The Japanese firms Toyota, Honda, and Nissan are the most central companies and belong to a larger international group comprised of Japanese, Chinese, Korean, and US companies. On the bottom left of the map, European manufacturers emerge, such as Volkswagen, Fiat, Porsche, Renault, BMW, PSA, and MAN, among which are India's Tata and the Soviet Avtovaz and the Malaysian Proton and its Lotus brand. Ford, GM, and Hyundai represent a technological bridge between the two areas. An important peculiarity of some company outliers such as Chrysler, Daimler AG, Geely, Volvo, and Chinese Saic and Dongfeng that belong to cluster 3 is seen, while peripheral positioning is occupied by Daewoo and Kia at the top right. The automakers that make up the current groups have sometimes focused more decentralized placement between them. The analysis relates how the level of similarity varies from group to group. Toyota, Hino, and Daihatsu have a significant distance in their positioning technology as well as the Hyundai group joined by Kia Motors in 1998. The Volkswagen group is heavily concentrated in the lower part of the map that houses companies like Audi and Porsche, but especially with the automotive manifacturers recently acquired as Porsche, Scania, and MAN as if to consolidate its position rather than acquiring technologies more distant. The group supported since 2001 by GM Daewoo has a high level of heterogeneity. Interesting is the distance in positioning between Nissan and Renault, despite the alliance that has joined the two groups since 1999. Among the Chinese automakers stands the central positioning of Faw Motor Company, probably due to the significant joint ventures with the Volkswagen and Toyota brands.

The technological positioning trends

The map shows an high sector technology structure concentration, with the exception of the Indian company Tata on the right side (Fig. 2). Ford, Toyota, and Renault are the major groups of centrality. Geely is the only Chinese enterprise present. Cluster analysis clearly shows six groups. General Motors is highly decentralized, a symptom of the uniqueness of its patent portfolio. Daimler and Hyundai are central, positioned in the two groups at the top along with the major Japanese companies, while at the bottom are MAN, Navistar, Volvo, and Paccar, which are all specialized in truck production, just below the European Union automakers. Interesting is the proximity of technology for Fiat and Chrysler, now belonging to the same group, and vice versa, the distance between Toyota and Daihatsu as separate companies at that time and since 1999 part of the same group. Of note is the proximity between Porsche and Volkswagen.

Finally, the Volvo Group, at this stage not yet divided between truck and car production, is positioned at the left side near Navistar.

The map transposes the effects of the Asian crisis of 1997–1998 and has a strong dispersion compared to the previous period's technology structures (Fig. 3). The distances between companies are larger.

To highlight the lack of a technological leader and a high level of technological heterogeneity, the central part of the map is empty. BYD, Geely, and Avtovaz represent the outliers in the areas to the right with low levels of concentration.

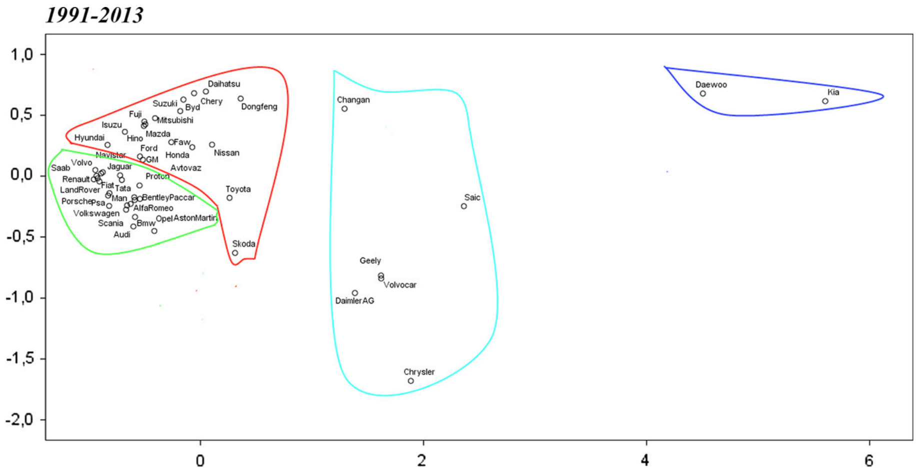

Fig. 1 Map obtained through multidimensional scaling and cluster analysis—firms technological positioning 1991–2013

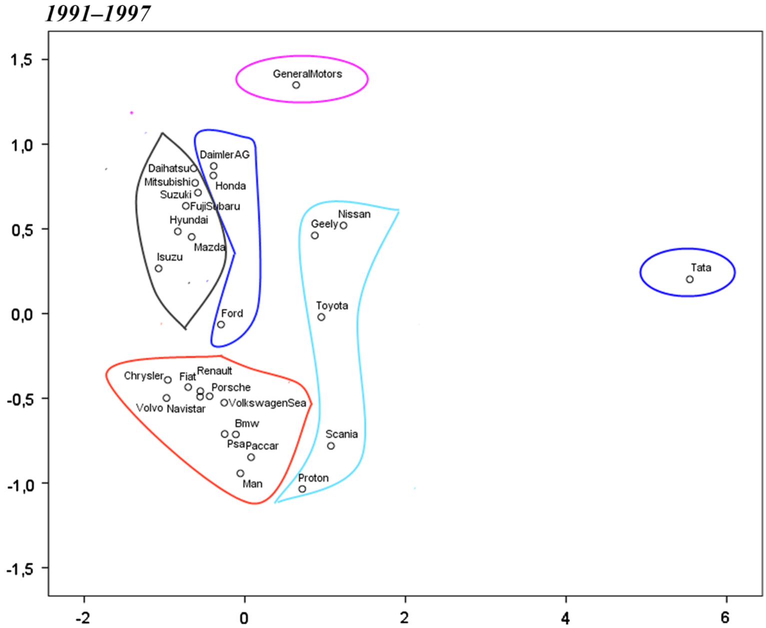

Fig. 2 Map obtained through multidimensional scaling and cluster analysis—automotive groups technological positioning 1991–1997

Toyota and Subaru Fuji lose their centrality compared to the previous period and depart significantly from Japanese firms showing strong technological differentiation from their competitors. Tata acquires centrality, while General Motors approaches Daimler AG and Nissan. Hyundai acquired Kia Motor Company, and now it is in a bridge position with Ford, while some American and European companies together with the Malaysian company Proton occupy the top left of the map. It confirms the proximity of technological

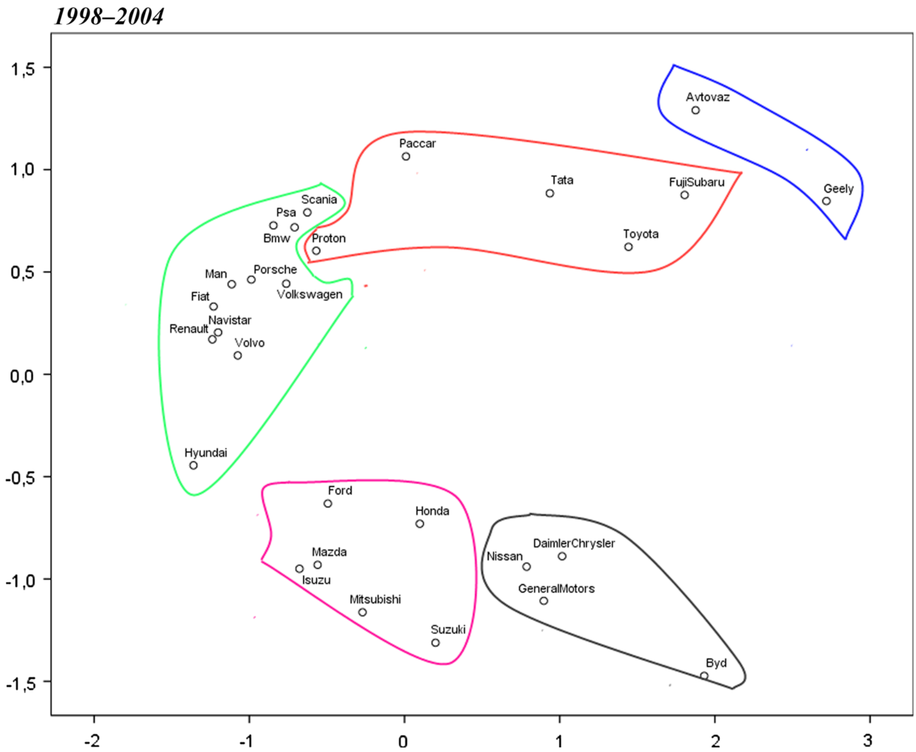

Fig. 3 Map obtained through multidimensional scaling and cluster analysis—automotive groups technological positioning 1998–2004

enterprises that form the Volkswagen group like Porsche, Scania, and MAN and the merger between Daimler and Chrysler. Daimler-Chrysler does not cause distortions in the particular positioning of Daimler AG. Cluster analysis clearly shows five groups with a highly heterogeneous level in terms of nationality composition with respect to the previous period. Toyota increases the distance between traditional Nissan competitors. Ford gets closer to Mazda, and Hyundai and Tata enter the Toyota cluster.

The map includes the effects of the strong economic performance and global sales of the previous 5 years to have a stronger concentration symptomatic of technological proximity than in the previous period (Fig. 4). During this period, Daimler AG, Ford, and GM occupy the most central locations on the map. General Motors, in particular, takes a decidedly opposite path in the three periods compared to Toyota. The American company tends to centralize its positioning technology, while Toyota tends to move within the confines of the map. Peripheral positions are occupied mainly by Chinese companies in this period, beginning to produce not only cars but also technology. Volvo and Renault approach its position, and Tata emerges and centralizes its position, probably due to the acquisition of the Jaguar and Land Rover brands. In this phase, Daimler and Chrysler return as two separate entities while maintaining proximity in technology. Cluster analysis clearly shows five groups. For the first time and probably because of strong joint ventures, Toyota and Volkswagen belong to a similar cluster with Faw Motor, the most centrally positioned Chinese firm. Chrysler, after the split with the Daimler AG group, joined the group of European companies as Ford; General Motors and Daimler are the automakers that bridge

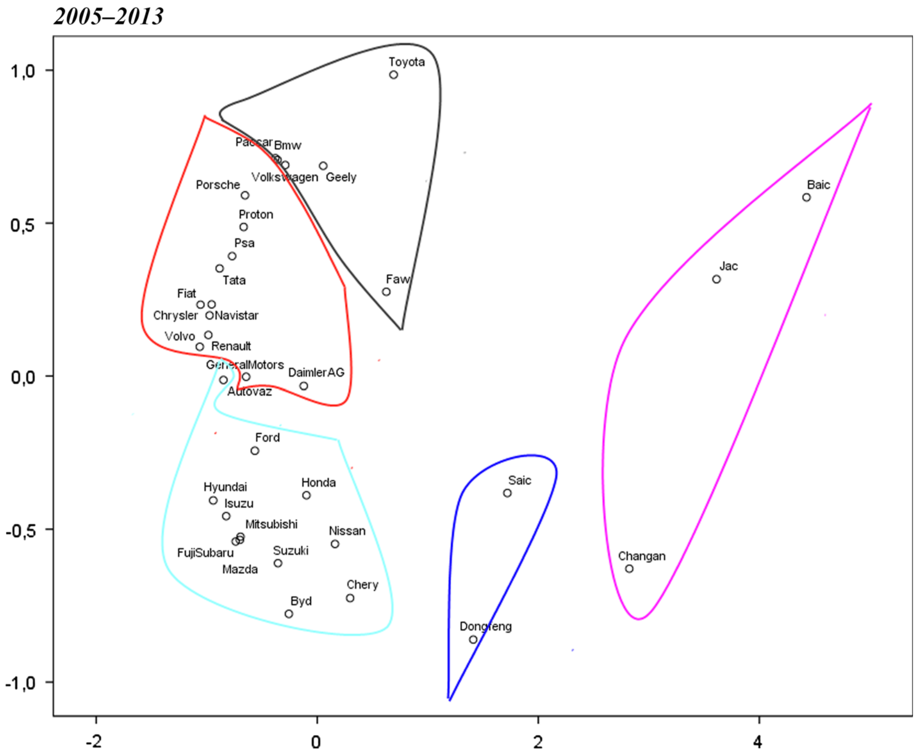

Fig. 4 Map obtained through multidimensional scaling and cluster analysis—automotive groups technological positioning 2005–2013

between the cluster at the bottom and those at the top. Finally, the two rising peripheral clusters on the right side of the map consist exclusively of Chinese enterprises.

Discussion

In this research, we propose a large patent co-citation cartography of the automotive industry. By screening and filtering the Derwent Innovation database, we selected data from about 581,000 patents, 1,309,356 citations, and 1,287,594 co-citations of 60 automotive assignees in the period of 1991–2013.

Because the players in the automotive sector are characterized by a strong propensity for strategic alliances, mergers and acquisitions, and joint ventures (Nohria and Garcia-Pont 1991), we made a historical analysis of the most relevant partnerships and deals that have involved firms since 1991. For the period of 1991–2013, we focused on single firms in order to be able to assess the contribution of each firm on patent portfolios in terms of group-similarity level. Then we divided the whole period into three sub-periods of 7 years (1991–1997; 1998–2004; and 2005–2013). Finally, an overall technology landscape and three sub-period maps were visualized.

Patent bibliometrics highlight substantial differences in the world's car production rankings. Essentially, the most efficient technology manufacturers do not coincide with the major manufacturing sellers. Car manufacturers mainly patented in the reference period are Toyota, Hyundai, and Honda, with 120,680, 87,428, and 55,801 patents, respectively.

The overall patent co-citation analysis shows an area of high concentration and technological similarities of firms. This is consistent with the high level of collective cognition typical of industries, such as the automotive industry, which is characterized by historical actors, high barriers to entry, and a long history of partnerships and alliances. Even the map of the first sub period (1991–1997) behaves the same way, while that of the second transposes the effects of the Asian crisis of 1997–1998 and has a strong dispersion. It seems that in a time of uncertainty, companies tend to seek their own way and do not follow the logic of isomorphism. In the third timespan, mainly characterized by periods of economic growth, the technological structure of the sector is again dense. For all of these reasons, the study fits into the interpretative approach of collective cognition, highlighting how the cartographic patent co-citation analysis could be adopted as a proxy of the industries' cognitive technological representations in times of stability and uncertainty. This exploratory study increases the awareness of scholars by detecting and visualizing the technology management phenomenon from two points of view: it provides a descriptive overview of the technological positioning of the firms and groups (micro-level), and analyzes the relationships between the technology structure and collective cognition of an entire sector at positive or negative economic scenarios (macro-level). It reveals innovation similarities and trends of assignees and groups, and makes it possible to hypothesize patent strategies and latent relationships among them.

Conclusion

In this paper, using patent co-citation analysis, we show how in the automotive industry (1) most of the companies are located close together, depicting the sector technology structure as highly dense; (2) the market leaders do not coincide with technology production leaders and do not necessarily occupy central technological positions; (3) the automotive groups considerably vary in the three timespans studied in terms of position and composition; (4) the market leader groups occupy technological remoteness positions during economic growth timespan; (5) the sector technology structure is highly dense during growth, and strongly scattered with a lack of technologically-centered positioned actors after economic decline.

In particular, these studies have shown more differences between the patent portfolios of companies in terms of quantity and quality. The companies with the most important patent portfolios quantitatively differ from those with a portfolio of more impact citations, demonstrating significant strategic and performance discrepancies between single companies and groups. Visualization and technology positioning maps of companies in the period from 1991 to 2013 and automotive groups in three seven-year periods open wide spaces to trail blaze. First, a contribution to the patent strategy and cognition literature has emerged on the basis of differences in positioning among companies and groups during the entire period, divided into timespans. In the overall map, this has emerged as some groups are composed of firms with heterogeneous positioning and consequently heterogeneous patent portfolios, while other groups have steadily increased over the years by acquiring high map closeness with companies with similar technological characteristics.

Moreover, the analysis of the three subdivided periods has highlighted how the level of similarity or distance among the groups, namely the collective cognition, changes continuously. The high concentration level that characterizes the first period is changed in the second, which is more dispersed and where there are no central or technological leader groups. Yet, the third period returns to a concentration level similar to the first period. Such behavior of the map, if considered in relation to the economic performance of the production and sales of the industry, reveals how, in times of crisis, companies tend to look for a heterogeneous technology portfolio to obtain competitive advantages, while in positive economic periods, conformity tends to prevail. It is as if the collective cognition profoundly affects the technology positioning and behaviour of firms at the expense of objective assessments of patent strategy decisions.

In addition, research has highlighted significant strategic differences in positioning in the various periods in which such central enterprises move to the suburbs and vice versa, and some change their technology cluster membership by moving into another and then finally emerge or disappear because of a failure or because of an M&A.

Finally, an explorative contribution originates from the evaluative study of the groups' conformation in terms of brands and partnership formal contracts. In fact, it opens new horizons to researchers who want to analyse the impact of M&As or JVs on technological map positioning. Fifth, this study offers a contribution to strategic cognition, patent strategy, and technology positioning literature by adopting an unusual and non-traditional methodological lens for assignees' patent co-citation analysis.

Several limitations must be mentioned. Although quite rigorous, co-citation analysis is subject to some limitations that can bias the results of the research if not properly addressed, namely, homogeneity, immediacy, and stability (Brown and Gardner 1985; Pierce 1990). Homogeneity refers to the fact that each research field has its own peculiarities, so the criteria for the selection of patent thresholds for co-citation analysis have to be targeted to the field. Immediacy regards the conservative nature of the analysis that is based on the accumulation of a sufficient number of citations for a patent to be included in the study. Instability involves the unavoidable fluctuations in research analysis and technologies over time.

References

Abraham, B. P., & Moitra, S. D. (2001). Innovation assessment through patent analysis. *Technovation, 21*(16757), 245–252.

Abrahamson, E., & Hambrick, D. C. (1997). Attentional homogeneity in industries: The effect of discretion. *Journal of Organizational Behavior, 18*(S1), 513–532.

Acedo, F. J., Barroso, C., & Galan, J. L. (2006). The resource-based theory: Dissemination and main trends. *Strategic Management Journal, 27*(7), 621–636.

Ahlgren, P., Jarneving, B., & Rousseau, R. (2003). Requirements for a cocitation similarity measure, with special reference to Pearson's correlation coefficient. *Journal of the American Society for Information Science and Technology, 54*(6), 550–560.

Archibugi, D., & Pianta, M. (1996). Measuring technological through patents and innovation surveys. *Technovation, 16*(9), 451–468.

Bensman, S. J. (2004). Pearson's r and author cocitation analysis: A commentary on the controversy. *Journal of the American Society for Information Science and Technology, 55*(10), 935.

Brockhoff, K. (1991). Competitor technology intelligence in German companies. *Industrial Marketing Management, 20*(2), 91–98.

Brockhoff, K. K., Ernst, H., & Hundhausen, E. (1999). Gains and pains from licensing patent-portfolios as strategic weapons in the cardiac rhythm management industry. *Technovation, 19*(10), 605–614.

Brown, L. D., & Gardner, J. C. (1985). Using citation analysis to assess the impact of journals and articles on contemporary accounting research (CAR). *Journal of Accounting Research, 23*(1), 84–109.

Castriotta, M, & Di Guardo, M. C. (2015). A collective reasoning on the automotive industry: A patent co-citation analysis. In *15th ISSI conference, Istanbul* (pp. 865–870).
Cheung, K. Y., & Ping, L. (2004). Spillover effects of FDI on innovation in China: Evidence from the provincial data. *China Economic Review, 15*(1), 25–44.
Cho, J. (2014). Intellectual structure of the institutional repository field: A co-word analysis. *Journal of Information Science, 40*(3), 386–397.
Culnan, M. J. (1986). The intellectual development of management information systems, 1972–1982: A co-citation analysis. *Management Science, 32*(2), 156–172.
Cyert, R. M., & March, J. G. (1963). *A behavioral theory of the firm*. Englewood Cliffs, NJ: Prentice-Hall. **2**.
Di Guardo, M. C., & Harrigan, K. R. (2012). Mapping research on strategic alliances and innovation: A co-citation analysis. *The Journal of Technology Transfer, 37*(6), 789–811.
Di Maggio, P., & Powell, W. W. (1983). The iron cage revisited: Collective rationality and institutional isomorphism in organizational fields. *American Sociological Review, 48*(2), 147–160.
Di Stefano, G., Gambardella, A., & Verona, G. (2012). Technology push and demand pull perspectives in innovation studies: Current findings and future research directions. *Research Policy, 41*(8), 1283–1295.
Eck, N. J. V., & Waltman, L. (2009). How to normalize cooccurrence data? An analysis of some well-known similarity measures. *Journal of the American Society for Information Science and Technology, 60*(8), 1635–1651.
Egghe, L., & Leydesdorff, L. (2009). The relation between Pearson's correlation coefficient r and Salton's cosine measure. *Journal of the American Society for Information Science and Technology, 60*(5), 1027–1036.
Ernst, H. (2003). Patent information for strategic technology management. *World Patent Information, 25*(3), 233–242.
Gibson, C. B. (2001). From knowledge accumulation to accommodation: Cycles of collective cognition in work groups. *Journal of Organizational Behavior*, 22(2), 121–134.
Hannan, M. T., & Freeman, J. (1977). The population ecology of organizations. *American Journal of Sociology, 82*(5), 929–964.
Hodgkinson, G. P., & Healey, M. P. (2008). Cognition in organizations. *Annual Review of Psychology, 59*, 387–417.
Hsiao, C. H., & Yang, C. (2011). The intellectual development of the technology acceptance model: A co-citation analysis. *International Journal of Information Management, 31*(2), 128–136.
Hu, C. P., Hu, J. M., Gao, Y., & Zhang, Y. K. (2010). A journal co-citation analysis of library and information science in China. *Scientometrics, 86*(3), 657–670.
Islam, G. (2015). Extending organizational cognition: A conceptual exploration of mental extension in organizations. *Human Relations, 68*(3), 463–487.
Jaffe, A. B. (1986). Technological opportunity and spillovers of R&D: evidence from firms' patents, profits and market value. *The American Economic Review, 76*, 984–1001.
Jeong, Y. K., Song, M., & Ding, Y. (2014). Content-based author co-citation analysis. *Journal of Informetrics, 8*(1), 197–211.
Johnson, D. R., & Hoopes, D. G. (2003). Managerial cognition, sunk costs, and the evolution of industry structure. *Strategic Management Journal, 24*(10), 1057–1068.
Kaplan, S. (2011). Research in cognition and strategy: Reflections on two decades of progress and a look to the future. *Journal of Management Studies, 48*(3), 665–695.
Kaplan, D. M. (2012). How to demarcate the boundaries of cognition. *Biology and Philosophy, 27*(4), 545–570.
Kaplan, S., & Tripsas, M. (2003). Thinking about technology: Understanding the role of cognition and technical change. Harvard Business School Working Paper Series (No. 03-007).
Kaplan, S., & Tripsas, M. (2008). Thinking about technology: Applying a cognitive lens to technical change. *Research Policy, 37*(5), 790–805.
Kay, L., Newman, N., Youtie, J., Porter, A. L., & Rafols, I. (2014). Patent overlay mapping: Visualizing technological distance. *Journal of the Association for Information Science and Technology, 65*(12), 2432–2443.
Kim, Y. G., Suh, J. H., & Park, S. C. (2008). Visualization of patent analysis for emerging technology. *Expert Systems with Applications, 34*(3), 1804–1812.
Kostoff, R. N., Stump, J. A., Johnson, D., Murday, J. S., Lau, C. G., & Tolles, W. M. (2006). The structure and infrastructure of the global nanotechnology literature. *Journal of Nanoparticle Research, 8*(3–4), 301–321.
Lai, K. K., & Wu, S. J. (2005). Using the patent co-citation approach to establish a new patent classification system. *Information Processing and Management, 2*, 313–330.

Leydesdorff, L., & Vaughan, L. (2006). Co-occurrence matrices and their applications in information science: Extending ACA to the web environment. *Journal of the American Society for Information Science and Technology, 57*(12), 1616–1628.
McCain, K. W. (1990). Mapping authors in intellectual space: A technical overview. *Journal of the American Society for Information Science, 41*(6), 433–443.
Mêgnigbêto, E. (2013). Controversies arising from which similarity measures can be used in co-citation analysis. *Malaysian Journal of Library & Information Science, 18*(2), 25–31.
Murray, F. (2002). Innovation as co-evolution of scientific and technological networks: Exploring tissue engineering. *Research Policy, 31*(8), 1389–1403.
Nadkarni, S., & Narayanan, V. K. (2007). Strategic schemas, strategic flexibility, and firm performance: The moderating role of industry clockspeed. *Strategic Management Journal, 28*(3), 243–270.
Narayanan, V. K., Zane, L. J., & Kemmerer, B. (2010). The cognitive perspective in strategy: An integrative review. *Journal of Management, 37*(1), 305–351.
Narin, F. (1994). Patent bibliometrics. *Scientometrics, 30*(1), 147–155.
Nerur, S. P., Rasheed, A. A., & Natarajan, V. (2008). The intellectual structure of the strategic management field: An author co-citation analysis. *Strategic Management Journal, 29*(3), 319–336.
Nohria, N., & Garcia-Pont, C. (1991). Global strategic linkages and industry structure. *Strategic Management Journal, 12*(S1), 105–124.
Pierce, S. J. (1990). Disciplinary work and interdisciplinary areas: Sociology and bibliometrics. In C. L. Borgman (Ed.), *Scholarly communication and bibliometrics* (pp. 84–106). Newbury Park, CA: Sage.
Porter, A., & Rafols, I. (2009). Is science becoming more interdisciplinary? Measuring and mapping six research fields over time. *Scientometrics, 81*(3), 719–745.
Porter, A. L., & Youtie, J. (2009). How interdisciplinary is nanotechnology? *Journal of Nanoparticle Research, 11*(5), 1023–1041.
Rafols, I., Porter, A. L., & Leydesdorff, L. (2010). Science overlay maps: A new tool for research policy and library management. *Journal of the American Society for Information Science and Technology, 61*(9), 1871–1887.
Ravikumar, S., Agrahari, A., & Singh, S. N. (2015). Mapping the intellectual structure of scientometrics: A co-word analysis of the journal Scientometrics (2005–2010). *Scientometrics, 102*(1), 929–955.
Rowlands, I. (1999). Patterns of author cocitation in information policy: Evidence of social, collaborative and cognitive structure. *Scientometrics, 44*(3), 533–546.
Schulze, A., Brojerdi, G., & Krogh, G. (2014). Those who know, do. Those who understand, teach. Disseminative capability and knowledge transfer in the automotive industry. *Journal of Product Innovation Management, 31*(1), 79–97.
Seol, H., Lee, S., & Kim, C. (2011). Identifying new business areas using patent information: ADEA and text mining approach. *Expert Systems with Applications, 38*(4), 2933–2941.
Shiau, W. L., & Dwivedi, Y. K. (2013). Citation and co-citation analysis to identify core and emerging knowledge in electronic commerce research. *Scientometrics, 94*(3), 1317–1337.
Shiau, W. L., Dwivedi, Y. K., & Tsai, C. H. (2015). Supply chain management: Exploring the intellectual structure. *Scientometrics, 105*(1), 215–230.
Small, H. (1973). Co-citation in the scientific literature: A new measure of the relationship between two documents. *Journal of the American Society for information Science, 24*(4), 265–269.
Sugimoto, C. R., Pratt, J. A., & Hauser, K. (2008). Using field cocitation analysis to assess reciprocal and shared impact of LIS/MIS fields. *Journal of the American Society for Information Science and Technology, 59*(9), 1441–1453.
Van Eck, N. J., & Waltman, L. (2008). Appropriate similarity measures for author co-citation analysis. *Journal of the American Society for Information Science and Technology, 59*(10), 1653–1661.
Wallace, M. L., Gingras, Y., & Duhon, R. (2009). A new approach for detecting scientific specialties from raw cocitation networks. *Journal of the American Society for Information Science and Technology, 60*(2), 240–246.
Wang, X., Zhang, X., & Xu, S. (2011). Patent co-citation networks of Fortune 500 companies. *Scientometrics, 88*(3), 761–770.
Wells, P., & Nieuwenhuis, P. (2012). Transition failure: Understanding continuity in the automotive industry. *Technological Forecasting and Social Change, 79*(9), 1681–1692.
West, G. P. (2007). Collective cognition: When entrepreneurial teams, not individuals, make decisions. *Entrepreneurship Theory and Practice, 31*(1), 77–102.
White, H. D. (2003). Author cocitation analysis and Pearson's r. *Journal of the American Society for Information Science and Technology, 54*(13), 1250–1259.

Yan, B. N., Lee, T. S., & Lee, T. P. (2015). Mapping the intellectual structure of the Internet of Things (IoT) field (2000–2014): A co-word analysis. *Scientometrics, 105*(2), 1285–1300.
Youtie, J., Shapira, P., & Porter, A. L. (2008). Nanotechnology publications and citations by leading countries and blocs. *Journal of Nanoparticle Research, 10*(6), 981–986.
Zapata, C., & Nieuwenhuis, P. (2010). Exploring innovation in the automotive industry: New technologies for cleaner cars. *Journal of Cleaner Production, 18*(1), 14–20.
Zhao, Q., & Guan, J. (2013). Love dynamics between science and technology: Some evidences in nanoscience and nanotechnology. *Scientometrics, 94*(1), 113–132.