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# Technology fusion: Identification and analysis of the drivers of technology convergence using patent data

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A B S T R A C T

The concepts of technology convergence or technology fusion describe the phenomenon of technology overlap. Despite evidence of the higher value associated to interdisciplinary research and cross-industry innovation, few studies have investigated the characteristics of technology fusion based on patent data. This study identifies new cases of convergence relying on the International Patent Classification (IPC) of patents filed at the European Patent Office between 1991 and 2007: the first occurrence of a patent incorporating a combination of IPC subclasses signals a new instance of fusion. Duration models are employed to investigate the impact of field level characteristics derived from patent bibliometrics on the likelihood of identifying a new fusion. The results show that merges are more frequent if the focal technology fields are closely related (based on a higher number of cross citations), are characterized by wide technological scope, and are the result of an inter-firm collaboration. In contrast to previous findings, the results show that the more complex the technologies involved, the less the likelihood of their convergence or fusion. The correlation between fusion likelihood and the characteristics of the merging fields could help managers and policymakers to predict the emergence of new technology areas.



## 1. Introduction

Technology convergence, fusion, merging, cross-fertilization, and hybridization are all terms used to address the phenomenon of technology overlap which Curran (2013) defines as the blurring of the boundaries between disjoint areas of science, technology, markets, or industries. The topic of technology fusion began to attract attention following Kodama's (1992) seminal piece, and evidence of the higher value associated with interdisciplinary research and cross-industry innovation. At the invention level, converging fields appear to be characterized by greater novelty and more breakthrough results (Schumpeter, 1939; Fleming, 2001; Hacklin, 2007; No and Park, 2010; Nemet and Johnson, 2012; Karvonen and Kässi, 2013); at the firm and sector levels, previous studies on merged fields observe better performance and a relevant impact on industry evolution since technology fusion sustains and revamps innovation trends and generates new trajectories (No and Park, 2010; Kim and Kim, 2012; Curran, 2013; Hacklin et al., 2013). Industry is evolving driven by the faster growth of the merging fields, and the disruptive elements of the products based on the converged technologies (Carnabuci, 2012; Kim et al., 2014).

Technology convergence began to attract attention in the 1980s and even more in the 1990s when diffusion and overlaps among robotics, computing, and information and telecommunication technologies began to have a significant impact on the products and strategies of firms in several industries from information and communication technology (ICT) to consumer electronics, to mechatronics (Kodama, 1992; Lind, 2004). Since then, several fields have been characterized by fusion dynamics (Pennings and Puranam, 2001; Curran, 2013). Telecommunications, ICT, and electronics spread to and merged with several other sectors (e.g., optoelectronics; innovations in packaging; printable electronics; RFID - radio frequency identification - tags; smart-phone, smart-television and smart-home). Chemicals combined with informatics, textiles and materials and these innovations have been competing with agricultural products. The pharmaceuticals industry collaborations have resulted in the emergence of biotechnology, bioinstrumentation and nanotechnology, nutraceuticals and functional foods, cosmeceuticals, and in services (e.g. health care management, insurance and banking) and the so-called "TIME" industry, based on overlaps among telecoms, information technology, media and entertainment (Lind, 2004; Hacklin et al., 2013). In some cases, a specific product has supported the development of other fields (Nemet and Johnson, 2012) such as steam engines, semiconductors, lasers and synthetic fibers.

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Merged fields are usually characterized by opportunities for firm growth based on successful capture and management of the available novel technologies, and competition with incumbents from new sectors (Kim and Kim, 2012). Companies that lack competences in these new fields may be forced to rely on external partners in cross-industry alliances or via a merger and acquisition (M&A) process (Lind, 2004). Definition of the corresponding firm strategies benefits significantly from an increased understanding of the role of technology innovation and the dynamics of the convergence process, especially in the case of disruptive trajectories (Bonnet and Yip, 2009).

Analysis of emerging overlapping trends in patent data, scientific publications, and firm classifications such as the Standard Industrial Classification (SIC) codes could help managers to identify and exploit new opportunities, avoid threats, plan future research and development (R&D) activity, and forecast technological trends in the transformation of industries (Choi et al., 2007; Kim and Kim, 2012; Hacklin et al., 2013; Karvonen and Kässi, 2013). From this perspective, the role of technological forecasting involving interdependencies across technologies, although a complex process can help firms to anticipate change and predict future needs (Jeong and Kim, 1997; Choi et al., 2007; Karvonen and Kässi, 2013). In particular, the study of technological interrelations can provide useful insights into the emergence of new technologies based on combinations of previous stand-alone technologies. More broadly, understanding technology fusion dynamics could be informative for the definition of science and technology policies, by enabling comparison among investments and other forms of support for interdisciplinary areas, with support for existing domains (Nemet and Johnson, 2012).

Several authors have proposed theoretical analyses, taxonomies and case studies of technological convergence (Gambardella and Torrisi, 1998; Nemet and Johnson, 2012; Curran, 2013; Hacklin et al., 2013). Although some propose theoretical methodologies (Pennings and Puranam, 2001; Kim and Kim, 2012) and explore specific technological fields based on data analysis (Choi et al., 2007; No and Park, 2010; Ko et al., 2014), there is no systematic empirical evidence on the overall characteristics of technology convergence. This article aims to fill this gap in two connected ways. First, it proposes a methodological approach to identifying the emergence of a fused technology based on the first combination of two International Patent Classification (IPC) codes, and applies this approach to a large data set of patents filed at the European Patent Office (EPO). Second, it investigates a set of patent-based characteristics, including the level of the linkages among technologies (the "converging process" in Curran, 2013), the technology cycle, and the complexity and value of the merging fields in order to understand their impact on the likelihood of a new fusion.

The article is organized as follows. Section 2 reviews the technology fusion literature and describes how patent data can be used to support empirical analysis and description of technological characteristics which have been theorized as relevant to the overlap processes. Section 3 describes data collection and methodology. Section 4 presents summary statistics and the results of the regression analyses and Section 5 discusses the results and provides some conclusions.

## 2. Research background

### 2.1. Previous literature on technology fusion

Two main research streams are distinguishable in the literature on technology fusion: work focusing on the theoretical aspects, and empirical case study exploration of specific fields and firm- and industry-level data analysis.

A number of studies in the first stream focus on the theoretical definition of convergence (e.g., Kodama, 1992; Hacklin, 2007). In particular, Curran (2013) organizes work on convergence starting from the definition and the usage of associated terms. He defines convergence (or fusion) as: "a blurring of boundaries between at least two hitherto disjoint areas of science, technology, markets or industries; [it creates] a new (sub-)segment […] as a merger of (parts of) the old segments" (Curran, 2013, p. 22).

Curran (2013) notes also the terms "convergence" and "fusion" have slightly different meanings. The former refers to a process in which two elements move towards a new common place; the latter implies that the two elements merge "in the very same place of at least one of the objects". Similar to Curran, this study uses these two terms interchangeably but highlights their difference if relevant to the analysis.

Among prior theoretical studies, the work of Pennings and Puranam (2001) is important because it paved the way to further research on the development of strategic and policy implications related to convergence. Pennings and Puranam's analytical framework distinguishes between demand side and supply side convergence. The latter is related to technological functionality, the former is associated with the contemporary satisfaction of different needs based on different technological capabilities which converged to become similar. Several authors have built on their seminal study. Bröring (2005) identifies additional categories such as "technology-driven input-side convergence" evolving from new technologies applied across different industries, and "market-driven output-side convergence" which occurs when customers start to consider products from different industries in a similar way (e.g., nutrients, dietary supplements, and herbal products included in the category of common food products). In the framework of evolutionary economics, Hacklin (2007) splits the process of convergence into four stages: knowledge, technology, application, and industry convergence. Curran (2013) notes the non-linearity of the process and suggests to consider the four stages as *loci* of convergence: science, technology, markets, and industries. This research is centered on the "technology" *locus* which corresponds to the supply side in Pennings and Puranam's (2001) framework and is motivated by the lack of work on technology convergence highlighted by Kim and Kim (2012).

Furthermore, the paucity of data on convergence between two technologies and the lack of an agreed indicator of interdisciplinarity limit the analysis of technology fusion (No and Park, 2010; Kim and Kim, 2012). Some empirical analyses of convergence employ concept frameworks, case studies or company-level data, in specific technological fields, to provide insights into corporate diversification. Hence, a broader wider approach to provide complementary evidence and extend work at the technology level is needed. The main contribution of the present study is twofold: to propose a method to identify technology convergence at system level relying on patent data and then to analyze the drivers of technology fusions.

### 2.2. Identification of technology fusion through patent data

Analysis of the convergence process among distinct technological fields requires a hierarchical structure to define domains (Murmann and Frenken, 2008; Roepke and Moehrle, 2013). A technological hierarchy enables measurement of technological distance and convergence. Coherently with the unit of analysis (industry, firm, technology), the investigation should rely on widely-accepted classifications such as SIC codes or International Patent Classification (IPC) codes, or on ad-hoc structures of specific keywords. The diffusion of Natural Language Processing tools has supported the analysis of convergence mechanisms in very specific technical fields delimited by sets of keywords (e.g. Roepke and

Moehrle, 2013; Kim et al., 2014, Ko et al., 2014). An alternative approach consists of defining a technological field on the basis of a group of selected companies (e.g. Karvonen and Kässi, 2013).

The technology convergence measure can be determined in terms of co-classification in the examined unit of analysis (e.g. multiple SIC or IPC codes in the examined companies or patents) or by considering the relationships among them (e.g. inter-firm alliances and M&As, patent citations) (Pennings and Puranam, 2001; Karvonen and Kässi, 2013). The increasing number of patent protected innovations in multiple technical fields is a sign of a process of convergence; other proxies are inter-sector collaboration, licensing activities, and scientific publications (Curran, 2013). This study analyzes technological convergence and accordingly makes use of patent data.

In studies of the technological aspects of convergence, patents have been employed to generate implications about technology fusion (Curran and Leker, 2011; Ko et al., 2014) for the following reasons. In general, patent data are considered up-to-date and reliable knowledge sources (Griliches, 1990; Trajtenberg et al., 1997), indicators of organizations' R&D activities and inventive activity within a technological field, and allow identification of technology trajectory and life cycle (Roepke and Moehrle, 2013; Ko et al., 2014). Patent data have been employed as indicators of technology convergence on the assumption that patent applications in a certain field represent an accumulation of knowledge and advancement in that technological trajectory (Karvonen and Kässi, 2013). Moreover, a single invention could trigger a process of convergence (Curran, 2013) that is a breakthrough embedding previously disjoint technologies (e.g., smart-tv). However, there are some limitations related to the use of patents (e.g. Harhoff et al., 1999; Choi et al., 2007; Nemet and Johnson, 2012): not all inventions are patentable and other forms of intellectual property (IP) protection might be employed; firms sometimes file patents strategically; patenting activities differ across industries, and patent law has changed over time.

Two features of patent data are particularly relevant to an investigation of convergence mechanisms: the hierarchical structure of the IPC codes, and the relationships formed by patent citations. IPC codes are assigned by the patent office examiners to patent filings according to the technical features of the inventions. Since the same document can be associated to several classes, the co-classification information can be used to identify the relationships between technologies (Choi et al., 2007; Kim and Kim, 2012; Karvonen and Kässi, 2013; Park and Yoon, 2014). Compared to Curran's (2013) definition of convergence, the IPC co-classification analysis more directly addresses the presence (or emergence) of a fusion, and to partly disregard the process of overlap between the two technology fields.

The IPC hierarchical structure resolves problems associated with identification based on keywords while also focusing the analyses on the technology rather than products or markets (Nemet and Johnson, 2012; Jaffe, 1986). In particular, selecting IPC subclasses (4-digit IPC codes) among the diverse aggregation levels of analysis provides an appropriate measure because it allows sufficient characterization of the technologies across a reasonable and treatable number of categories (van Zeebroeck et al., 2006; Park and Yoon, 2014). Several studies rely on this level of IPC hierarchy (Benner and Waldfogel, 2008; Nemet and Johnson, 2012; Choi et al., 2007).

However, IPC codes have some limitations. The IPC scheme does not cover all existing technological fields, e.g. it does not include software (the study focuses on the EPO), and refers to both the technologies and their application domains which in some cases might be misleading, for instance if the inventions are related to tools that can be applied in different fields, or if they include generic residual fields. Also, the IPC has changed over time: in our analysis, the most relevant specificities across releases such as inclusion (or exclusion) of a new (old) IPC subclass, have been taken into consideration. Similarly, the potential heterogeneity across the patent offices might be an issue which in this study is addressed in part by focusing only on the EPO. However, the forward and backward citations are from world offices.

The second feature of patent data which integrates the analysis of convergence mechanisms is the network of relationships formed by patent citations. Patent citation networks have been considered an alternative method to investigate convergence (Pennings and Puranam, 2001; Hacklin, 2007; No and Park, 2010; Nemet and Johnson, 2012; Roepke and Moehrle, 2013) since they help to identify between flows and trajectories (Trajtenberg, 1990; Jaffe et al., 1998; Hall et al., 2001; Kim et al., 2014) especially in scientific disciplines. Research fields increasingly citing each other's publications will eventually develop closer research collaborations (Karvonen and Kässi, 2013). Thus, the analyzed convergence is more basic and might not determine a complete fusion. In Curran's (2013) definition the measurement appears more appropriate to the overlapping process as the "stretching of one field to another", rather than to a fusion event.

The characteristics of patent data have been used to measure technological convergence. There is a group of studies which does not directly employ the terms "fusion" and "convergence" but investigate technological proximity and combination relying on patent classification based measures. Trajtenberg et al. (1997) compute a dis-similarity measure exploiting the US patent classes of the citing and cited patents. Fleming (2001) studies the familiarity of inventors with the combinations of the technical components of an invention (i.e., the IPC subclasses).

Among works specifically on technological convergence, the most frequent method relies on the patent citation or co-classification analysis (Lee et al., 2009; No and Park, 2010; Ko et al., 2014; Kim et al., 2014; Choi et al., 2007; Jun, 2013; Nemet and Johnson, 2012; Park and Yoon, 2014) to generate a matrix in which the columns and rows are different patent classes, and each matrix cell reports a measure based on a count of the patents connecting the two (column and row) patent classes. The matrix supports the definition of maps or network graphs (Kim and Kim, 2012; Ko et al., 2014; Park and Yoon, 2014), and allows the calculation of indexes measuring technological convergence more or less directly. Choi et al. (2007) base their methodological approach on a patent-based cross-impact analysis which converts the generated matrix into a network graph in order to estimate a directional index of the impact of one technology on another. This index corresponds to the "support" measure in the work of Jun (2011) who employs an Association Rule Mining approach to calculate a composite index for pairs of IPC classes. Park and Yoon (2014) rely on analytic network process and social network analysis to estimate the coreness and intermediarity of technology sectors, and to generate knowledge spillover portfolio maps. Kim and Kim (2012) model the technological convergence analysis distinguishing between knowledge convergence, based on citation analysis, and two patent indexes, intensity and coverage, based on the co-classification analysis. The former measures the strength of convergence between two technologies by considering the number of co-classified patents. The coverage index for a certain technology is an indication of the degree of co-classification with any other technology.

### 2.3. Drivers of technology fusion

The literature theorizes about potential drivers of technology convergence, providing evidence from case studies and firm- and industry-level empirical approaches. Some technology characteristics such as size, maturity, diffusion (Carnabuci, 2012; Curran, 2013; No and Park, 2010) and the complexity of technological content (Curran, 2013; No and Park, 2010) are considered to have a positive effect on the occurrence of a fusion event. Also, industries characterized by multiple application domains, digitization and miniaturization processes, or innovation based on new product architecture are considered to be favorable to technological fusions (No and Park, 2010; Curran, 2013).

Among the drivers of technology fusion, Curran (2013) includes the managerial role, and the propensity for inter-firm collaborations which assumes particular relevance in the case of a paradigm shift from production to R&D companies.

Finally, science-based sectors which are closer to basic research, might be more influenced by the technology overlap process (Karvonen and Kässi, 2013). However, Meyer (2000a, 2000b) suggests caution when considering non-patent citations because they might have been added by the applicant in an attempt to increase the breadth of patent coverage, or added by the examiner as standard practice for certain fields.

As Ko et al. (2014) highlight, previous studies are not sufficiently focused on how technological knowledge flows across industries, and there is no systematic empirical work on technology convergence. Against this background, the present study tries to expand understanding of the process of technological convergence by investigating the relevance of technology level drivers of new technology fusions.

## 3. Methodology

The definition of technology fusion operationalized in this study is based on the co-classifications of 4-digit IPC codes: the first occurrence of a combination of two IPC subclasses is considered to indicate the birth of a converged technology. This approach is similar to that employed in studies that propose a matrix of occurrences in a particular year. The definition of convergence adopted in this study is consistent with the general definition proposed by Curran (2013) and refers to the particular application as the status of technological evolution which is in line with the characterization suggested by several authors (Fleming, 2001; Nemet and Johnson, 2012; Karvonen and Kässi, 2013): the technology fusion combines two or more existing technologies to produce a hybrid breakthrough.

The analysis is based on PATSTAT data (2014 release, CRIOS edition - see Coffano and Tarasconi, 2014). The sample includes all EPO patents with earliest priority year from 1991 to 2007 (years chosen for data integrity reasons). Focusing on one patent office allows to analyze consistent data (patent examiners will follow the same examination rules and guidelines). The time frame excludes recent years due to publication delays and missing data. The bibliometrics commonly used in literature are defined for each patent: number of different IPC subclasses, count of applicants and inventors, number of backward patent and non-patent citations, citations received in the five years following patent publication. In order to provide a superior hierarchical structure associated to the main industry sectors, the IPC codes have been matched to the corresponding technological classification of the WIPO (World Intellectual Property Organization) Concordance Table (WIPOConc) (Johnson, 2002). Also, for each EPO patent, all the cited patents and their relevant bibliometrics were retrieved.

The collected EPO patent applications total over 2.2 million, and the total number of different cited patents is around 4 million. More than half of analyzed EPO patents report more than one IPC subclass. In the context of the present study, note that 570 different 4-digit IPC codes have been assigned among the whole sample of selected EPO patents for a total of 180,300 potential combinations of pairs of IPC subclasses. Mirror combinations "AB"-"BA" were counted only once and the IPC subclasses created or concluded in the analyzed time frame were excluded: a total of 63 IPC subclasses, including Biotech fields, were dropped (e.g.: A01P B81B C13C F21P etc.). The focal time frame ranges from 1991 to 2007; all the fusions retrieved in the years before 1991 (21% of all the available potential combinations) are considered as already existing.

## 4. Results

Table 1 provides summary counts derived from the methodology applied. At the beginning of the examined period, 1991, a total of 143,149 pairs of different IPC subclasses (row 1 in Table 1) were available as potentially new combinations: no patents with similar pairs of IPC codes were filed at the EPO between 1978 and 1990. Analysis of the years up to 2007 reveals that 23,086 pairs of technology fields, 13% of all the potential combinations (row 2) were covered by at least one patent for the first time.

In order to consider the "converging process" (Curran, 2013) and the technological flows, the backward patent citations between each pair of fields were analyzed in line with Benner and Waldfogel (2008) and Nemet and Johnson (2012). For each pair of IPC subclasses "X" and "Y" in every sampled year, the backward citations of the corresponding patents were identified. Note that more than 90% of the EPO patents in the sample report at least one backward citation. The number of patents in the IPC subclass "X" citing the patents in IPC "Y" (and "Y" citing "X") was calculated for each patent: previous citations across the two technology classes can be considered a proxy for the level of convergence, that is, the stretching of one technology towards another in each examined pair. The patent-level numbers were aggregated at the level of technological field (4-digit IPC code) and the yearly average value was calculated by applying a perpetual inventory method with a 15% depreciation rate (variable "CONVERG_LVL") in order to account for the persistent effects of knowledge similar to Hall et al. (2010). The preliminary findings show that only 5.9% of the fusions identified have no cross-citations (i.e. neither of the two merged technologies has been involved in a mutual citation in a prior patent) until the moment of birth. The evidence supports the presence of a correlation between the convergence process and the final merging of the two fields considered.

Among the potential combinations for which no patent was filed in the examined time frame (row 3), more than half (58.5%) are characterized by the absence of any linkage in terms of cross citations (row 3.1). However, the same evidence can be read as half of the non-occurred fusions involve technological fields which have a history of cross citation.

Fig. 1 shows the cumulated yearly number of new fusions among all the recorded new fusions.

The analysis of technological distance between merging fields shows that 83.0% of the fused IPC subclasses are in different IPC sections (i.e., the first digits of the codes are different), thus generally in distant areas. The eight sections are: A, Human Necessities; B, Performing Operations, Transporting; C, Chemistry, Metallurgy; D, Textiles, Paper; E, Fixed Constructions; F, Mechanical

**Table 1**
Summary results on the sample of EPO patents from 1991 to 2007.

| Row | Identified fusions | Number | Percent |
|---|---|---|---|
| **(1)** | Total combinations in 1991 (all potentially new fusions) | 143,149 | 100.0% |
| **(2)** | New fusions occurred between 1991 and 2007 | 23,086 | 12.8% |
| **(2.1)** | No cross-citing until birth | 1,369 | 5.9% of (2) |
| **(3)** | No fusion occurred between 1991 and 2007 | 120,063 | 83.9% |
| **(3.1)** | No cross-citing in the time frame | 70,201 | 58.5% of (3) |

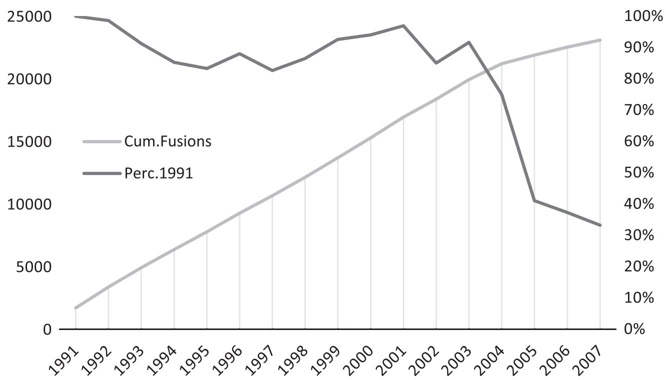


**Fig. 1.** Cumulated yearly number of identified new fusions as combination of IPC subclasses on the left axis and yearly values as percentage on year 1991 on the right axis.

Engineering, Lighting, Heating, Weapons; G, Physics; H, Electricity. In order to provide a more accurate evaluation of the differences between merged and not-merged, a measure was computed similar to the backward-looking proximity indicator of a technology proposed in Trajtenberg et al. (1997). Technological distance is determined by the following formula:

TECH_DIST = IPC1_DIST * $w_1$+ IPC3_DIST * $w_2$+ WIPO5_DIST * $w_3$+ WIPO35_DIST * $w_4$.

where IPC1_DIST, IPC3_DIST, WIPO5_DIST and WIPO35_DIST are dummies equal to 1 when the merged technical fields have respectively different IPC sections (first digit), IPC classes (3-digit code), WIPOConc areas (5 categories) or fields (35 categories). The WIPOConc classification groups all the 4-digit IPC codes into 35 fields of activities belonging to five macro areas: "Electrical engineering", "Instruments", "Chemistry", "Mechanical engineering" and "Other fields". The weights $w$ in the technological distance formula are set to 0.3, 0.2, 0.3 and 0.2 for respectively $w_1$ $w_2$ $w_3$ and $w_4$. Tests with different combinations of weights showed very similar results in the following econometric models (available on request). The values are defined in order to account for two characteristics: difference in IPC section or in WIPO sector represents a larger distance in the technological space; if the IPC section is different, then the IPC classes also are different, and similarly, if WIPO5_DIST is different, then WIPO35_DIST also is different. Table 2 provides examples of the potential values of the technological distance as previously defined.

Analysis of the distribution of TECH_DIST shows that the average distance for the sample of new fusions is 0.86, 66% higher than the value for the sample of not fused fields, and significantly different (the p-value of the t-test on the mean difference is significant at the 99% level). According to this preliminary evidence, the expected impact of technological proximity measured through hierarchical classifications on the probability to identify a new fusion is positive.

### 4.1. Industry level analyses

The five technological macro areas of the WIPOConc were examined to evaluate where the identified convergence occurred more frequently. The most frequent domain involved in 56.6% of the newborn fusions, is "Mechanical engineering" while the least frequent is "Instruments" (20.9% of cases). Table 3 reports the shares of fusions involving each combination of technological areas: the most frequent overlaps occur between "Mechanical engineering" and "Chemistry" (17.2%) followed by all the available matches with this field (e.g., inside the boundaries of the "Mechanical Engineering" merges occurred in 16.7% of cases). Among the other areas, fusions in the "Chemistry" field boundaries represent 5.4% of cases and the overlaps between "Chemistry" and "Electrical engineering" represents 4.7%.

Among more fine-grained statistics, the next set of figures shows fusion trends in 6 technology industries selected from among the 35 WIPOConc fields, for their different patterns. Although the size of the phenomenon is different (e.g., more fusions are identified in the field of "Transport" than in "Telecommunications"), and by definition, the yearly number of new fusions is decreasing, it is possible to visualize different trends. (Table 4).

Tables 5 and 6 show the most frequent fields involved in the convergence process among the 3-digit IPC classes and respective 4-digit IPC subclasses. Almost 8% of the new fusions involved the technical class "Measuring; testing" (G01), followed by B60 "Vehicles in general" (6.7%). It is interesting that the most frequent fields are connected to high-tech industries such as classes in the ICT sector (e.g. new developments in Electricity – H01 and H02 – or in Electric Communication – H04) and also apparently low-tech areas (e.g. Agriculture and Forestry – A01 – or Furniture – A47) where it is likely that radical new technical advances have been applied to more mature technologies.

On a more detailed level, Table 6 shows that some of the fields with the most overlap events are connected to data processing

**Table 2**
Examples of application of the formula of technological distance (TECH_DIST) between two fields, IPC x and IPC y.

| IPC subclass and description | IPC Section | IPC class | WIPO Sector | WIPO Field | TECH_DIST |
|---|---|---|---|---|---|
| B64B: Lighter-than-air aircraft | B | B64 | Mechanical Engineering | Transport | |
| B64C: Aeroplanes; helicopters | B | B64 | Mechanical Engineering | Transport | |
| Comparison between B64B and B6AC | Same | Same | Same | Same | 0.0 |
| | IPC1_DIST=0 | IPC3_DIST=0 | WIPO5_DIST=0 | WIPO5_DIST=0 | |
| A21D: Treatment, of flour or dough for baking […] | A | A21 | Chemistry | Food chemistry | |
| A23B: Preserving meat, fish, eggs, fruit, vegetables […] | A | A23 | Chemistry | Food chemistry | |
| Comparison between A21D and A23B | Same | Different | Same | Same | 0.2 |
| | IPC1_DIST=0 | IPC3_DIST=1 | WIPO5_DIST=0 | WIPO5_DIST=0 | |
| C07C: Acyclic or carbocyclic compounds | C | C07 | Chemistry | Organic fine chemistry | |
| C08B: Polysaccharides; derivatives thereof | C | C08 | Chemistry | Macromolecular chemistry | |
| Comparison between C07C and C08B | Same | Different | Same | Different | 0.4 |
| | IPC1_DIST=0 | IPC3_DIST=1 | WIPO5_DIST=0 | WIPO5_DIST=1 | |
| B21B: Rolling of metal | B | B21 | Mechanical Engineering | Machine Tools | |
| F01K: Steam engine plants; steam accumulators […] | F | F01 | Mechanical Engineering | Engines, pumps, turbines | |
| Comparison between B21B and F01K | Different | Different | Same | Different | 0.7 |
| | IPC1_DIST=1 | IPC3_DIST=1 | WIPO5_DIST=0 | WIPO5_DIST=1 | |

**Table 3**
Share of fusions involving each WIPO Concordance Table area and their combinations.

| | WIPO Concordance Table Areas | % of fusions involving the sector on total (%) | Fusions % with 1 (%) | Fusions % with 2 (%) | Fusions % with 3 (%) | Fusions % with 4 (%) | Fusions % with 5 (%) |
|---|---|---|---|---|---|---|---|
| 1 | Electrical engineering | 22.0 | 1.2 | | | | |
| 2 | Instruments | 20.9 | 2.8 | 1.1 | | | |
| 3 | Chemistry | 34.5 | 4.7 | 4.6 | 5.4 | | |
| 4 | Mechanical engineering | 56.6 | 10.2 | 9.3 | 17.2 | 16.7 | |
| 5 | Other fields | 25.7 | 3.8 | 3.7 | 5.4 | 11.6 | 2.4 |

**Table 4**
Charts of the trend of identified fusions in selected technological fields based on the WIPO Concordance Table. The continuous line represents the yearly number of new merges in percentage with respect to 1991; the dotted line represents the cumulate number of occurred fusions.

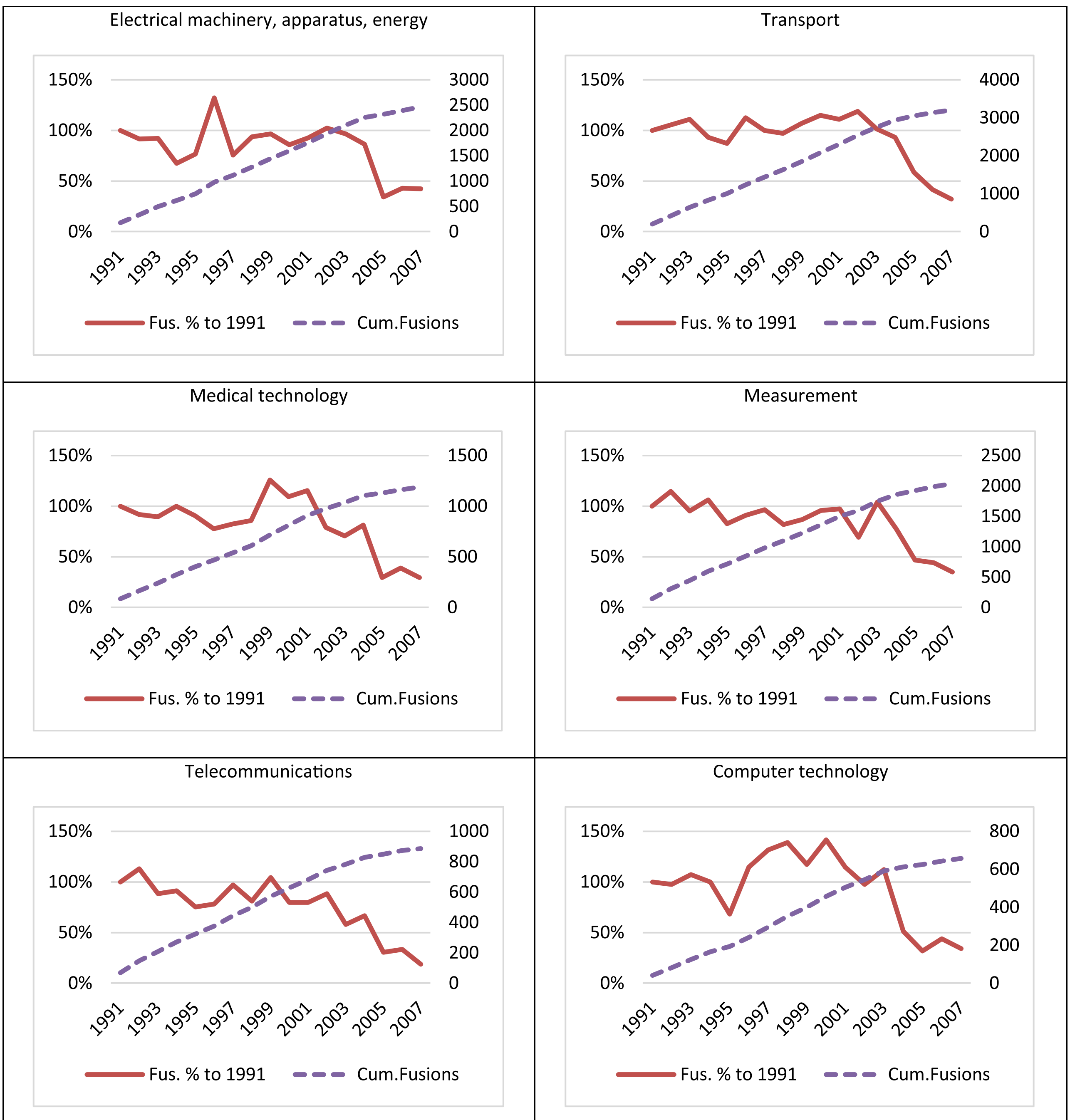

**Table 5**
Top 10 IPC classes by number of identified fusions in the years from 1995 to 2007.

| IPC3 | Description | Fusions | Perc. (%) |
|---|---|---|---|
| **G01** | Measuring; testing | 1820 | 7.9 |
| **B60** | Vehicles in general | 1551 | 6.7 |
| **H01** | Basic electric elements | 1402 | 6.1 |
| **A61** | Medical or veterinary science; hygiene | 1278 | 5.5 |
| **F16** | Engineering elements or units; general measures for producing and maintaining effective functioning of machines or installations; thermal insulation in general | 1199 | 5.2 |
| **H04** | Electric communication technique | 1079 | 4.7 |
| **A01** | Agriculture; forestry; animal husbandry; hunting; trapping; fishing | 986 | 4.3 |
| **A47** | Furniture; domestic articles or appliances; coffee mills; spice mills; suction cleaners in general | 925 | 4.0 |
| **H02** | Generation, conversion, or distribution of electric power | 857 | 3.7 |
| **C12** | Biochemistry; beer; spirits; wine; vinegar; microbiology; enzymology; mutation or genetic engineering | 814 | 3.5 |

(G06F, G06K), transmission (H04B, H04L, H04M) and new methods of energy generation and storage (H01M, F04B).

The majority of the fields where new fusions are most frequent match the industries identified in the literature (e.g., Pennings and Puranam, 2001; Curran, 2013) although many of the most cited examples are not among the retrieved merged fields. The reasons for this might be that the industries considered as case studies of convergence might have embarked on the fusion process before 1991 (e.g. Mechatronics), their specific IPC codes were created in the time frame analyzed, and thus are excluded (e.g. Biotech), or the convergence process was not associated with a sufficient number of patents (e.g. Food and Service industries) to rank among the most frequent categories.

### 4.2. Impact of technology level drivers of new fusions

The econometric analyses consist of survival-time models which account for the fact that non-fusing pairs might merge in the future. The regressions investigate empirically the impact of a number of patent variables, proxies for technological characteristics, on the likelihood of a first merge between a certain technological field X with another field Y.

The analyses aim to test the relevance of the convergence process previously defined as the yearly average of the deflated stock of cross-citations (CONVERG_LVL). All other patent-level variables are calculated as the average of the mean values computed for each of the two potentially merging fields, extending their invention-level interpretation to the field level, through aggregation of IPC subclasses.

The technological cycle (TECH_CYCLE) of a field is expressed by considering the yearly average age of the cited patents, similar to the measures in Kayal (1999) and Karvonen and Kässi (2013). A shorter time between citing and cited patents in a certain field suggests that the more recent technological area (the citing field) was able to absorb the new technologies (the cited ones) rapidly.

The previous literature (van Zeebroeck and van Pottelsberghe, 2011) distinguishes the characteristics of patent protected inventions along the dimensions of complexity and value which can be associated to specific patent level variables. Complexity can be measured by the number of backward patent (BWD_CIT) and non-patent citations (SCIENCE), of inventors (INVENTORS), and of reported IPC subclasses (TECH_SCOPE). Particular attention should be paid to non-patent citations, since the evidence in the literature is mixed. On the one side as Karvonen and Kässi (2013) note, the count of scientific citations estimates the proximity level of the linkages between scientific research and technological innovation as a proxy for the science intensity of R&D activities in the field. On the other side Meyer, (2000a, 2000b) suggests caution when considering non-patent citations because they might have been added by the applicant in an attempt to increase the breadth of patent coverage, or added by the examiner as standard practice for certain fields. Furthermore, the field-level average of the reported number of different 4-digit IPC codes represents technological scope: the propensity of the field to be transversal or multipurpose with applications in multiple technological domains, is expected to be positively associated to the likelihood of identifying a new fusion.

The following patent variables connected to value and ownership were included in the model to explore whether new fusions are associated to higher average technical merit of the merging fields, and whether more collaborative environments are linked to the emergence of new fusions. The mean number of patent assignees (ASSIGNEES) suggests the level of collaborativeness. The geographical scope (GEO_SCOPE) is based on the number of different countries to which the patent provides protection: additional countries imply additional fees and maintenance costs, thus this variable proxies for both market breadth and - indirectly - value. The count of citations received (FWD_CIT) is a measure of the technical merit of the protected inventions.

Additional controls are included: size of the technological field (SIZE), as the yearly average of patent stocks calculated using the perpetual inventory method for each pair of technical fields examined; technological distance (TECH_DIST) as the linear combination of the differences in the IPC hierarchical structure; sector (based on the 35 groups of the WIPOConc) and time dummies to take account of industry specificities which might be relevant to the convergence process and the global shift from manufacturing to R&D (Curran, 2013).

Table 7 presents summary statistics for the variables examined. The variance inflation factor analysis excludes collinearity and is available on request.

**Table 6**
Top 10 IPC subclasses by number of identified fusions.

| IPC4 | Description | Fusions | Perc. (%) |
|---|---|---|---|
| **H04L** | Transmission of digital information, e.g. Telegraphic communication | 199 | 0.9 |
| **G06F** | Electric digital data processing | 180 | 0.8 |
| **H01M** | Processes or means, e.g. Batteries, for the direct conversion of chemical energy into electrical energy | 159 | 0.7 |
| **G06K** | Recognition of data; presentation of data; record carriers; handling record carriers | 158 | 0.7 |
| **C12N** | Micro-organisms or enzymes; compositions thereof; propagating, preserving, or maintaining micro-organisms; mutation or genetic engineering; culture media | 151 | 0.7 |
| **H04M** | Telephonic communication | 151 | 0.7 |
| **B08B** | Cleaning in general; prevention of fouling in general | 147 | 0.6 |
| **F04B** | Positive-displacement machines for liquids; pumps | 145 | 0.6 |
| **G01C** | Measuring distances, levels or bearings; surveying; navigation; gyroscopic instruments; photogrammetry or videogrammetry | 145 | 0.6 |
| **H04B** | Transmission | 143 | 0.6 |

**Table 7**
Description and summary statistics of the examined variables.

| Variable | Description | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| **CONVERG_LVL** | Level of convergence expressed in terms of stock of cross-citations (calculated with perpetual inventory method) and aggregated as average of the yearly mean of the number of citations the field X received from field Y for the pair of potentially merging technological fields X and Y and vice versa (in logarithm) | 2,227,559 | 0.089 | 0.255 | 0.000 | 5.236 |
| **SIZE** | Average of the yearly stock of patents (calculated with perpetual inventory method) in the examined pair of fields (in logarithm) | 2,227,559 | 5.203 | 1.183 | 0.000 | 9.334 |
| **TECH_DIST** | Technological distance based on the differences of the IPC and WIPOConc classifications | 2,227,559 | 0.880 | 0.200 | 0.000 | 1.000 |
| **TECH_CYCLE** | Technology cycle or absorption speed: 5 year moving average of the yearly mean of the priority years of the cited patents for the pair of potentially merging technological fields X and Y (in logarithm) | 1,535,623 | 2.187 | 0.316 | 0.490 | 3.400 |
| **BWD_CIT** | 5 year moving average of the yearly mean of the number of backward patent citations for the pair of potentially merging technological fields X and Y (in logarithm) | 1,620,529 | 1.889 | 0.109 | 1.241 | 2.874 |
| **SCIENCE** | 5 year moving average of the yearly mean of the number of backward non-patent citations for the pair of potentially merging technological fields X and Y (in logarithm) | 1,620,529 | 0.692 | 0.204 | 0.147 | 2.359 |
| **TECH_SCOPE** | 5 year moving average of the yearly mean of the number of 4-digit IPC codes for the pair of potentially merging technological fields X and Y (in logarithm) | 1,620,529 | 1.305 | 0.123 | 0.788 | 1.886 |
| **INVENTORS** | 5 year moving average of the yearly mean of the number of inventors for the pair of potentially merging technological fields X and Y (in logarithm) | 1,618,379 | 1.186 | 0.107 | 0.760 | 1.716 |
| **ASSIGNEES** | 5 year moving average of the yearly mean of the number of assignees for the pair of potentially merging technological fields X and Y (in logarithm) | 1,620,529 | 0.730 | 0.018 | 0.693 | 0.921 |
| **FWD_CIT** | 5 year moving average of the yearly mean of the number of received citations in the first 5 years after publication for the pair of potentially merging technological fields X and Y (in logarithm) | 1,620,529 | 0.536 | 0.190 | 0.000 | 1.731 |
| **GEO_SCOPE** | 5 year moving average of the yearly mean of the number of countries where the patent has been extended to for the pair of potentially merging technological fields X and Y (in logarithm) | 1,620,529 | 1.960 | 0.127 | 1.504 | 2.615 |

**Table 8**
Results of the survival model on the likelihood to identify a new technology fusion: hazard rates are shown. Standard errors in parentheses. P value: *** $p < 0.01$,** $p < 0.05$,* $p < 0.10$.

| VARIABLES | (1) Model | (2) Model | (3) Model | (4) Model | (5) Model | (6) Model |
|---|---|---|---|---|---|---|
| CONVERG_LVL | 9.691*** | 9.274*** | 9.408*** | 9.389*** | 9.454*** | 9.442*** |
| | (0.072) | (0.076) | (0.079) | (0.079) | (0.080) | (0.080) |
| TECH_CYCLE | | 1.032 | 0.995 | 1.016 | 1.021 | 1.070 |
| | | (0.040) | (0.044) | (0.045) | (0.048) | (0.050) |
| BWD_CIT | | | 0.382*** | 0.358*** | 0.424*** | 0.400*** |
| | | | (0.041) | (0.038) | (0.046) | (0.043) |
| SCIENCE | | | 0.535*** | | 0.550*** | |
| | | | (0.038) | | (0.040) | |
| TECH_SCOPE | | | 2.738*** | 2.375*** | 3.168*** | 2.781*** |
| | | | (0.258) | (0.219) | (0.310) | (0.268) |
| INVENTORS | | | 0.460*** | 0.337*** | 0.535*** | 0.394*** |
| | | | (0.063) | (0.045) | (0.076) | (0.054) |
| ASSIGNEES | | | 17.082*** | 3.551** | 18.687*** | 5.071*** |
| | | | (10.517) | (2.123) | (11.608) | (3.086) |
| GEO_SCOPE | | | | | 0.547*** | 0.527*** |
| | | | | | (0.055) | (0.053) |
| FWD_CIT | | | | | 0.935 | 1.032 |
| | | | | | (0.065) | (0.071) |
| SIZE | 1.347*** | 1.289*** | 1.338*** | 1.331*** | 1.336*** | 1.326*** |
| | (0.011) | (0.012) | (0.014) | (0.013) | (0.014) | (0.014) |
| TECH_DIST | 0.902** | 0.936 | 0.923* | 0.933 | 0.927 | 0.935 |
| | (0.038) | (0.044) | (0.043) | (0.044) | (0.043) | (0.044) |
| Year dummies | Y | Y | Y | Y | Y | Y |
| Industry dummies | Y | Y | Y | Y | Y | Y |
| Constant | 0.005*** | 0.005*** | 0.002*** | 0.007*** | 0.002*** | 0.008*** |
| | (0.002) | (0.002) | (0.001) | (0.003) | (0.001) | (0.004) |
| Observations | 2,084,410 | 1,535,623 | 1,535,076 | 1,535,076 | 1,535,076 | 1,535,076 |
| loglike | −43,756 | −30,857 | −30,713 | −30,754 | −30,695 | −30,730 |
| chi2 | 73,974 | 58,286 | 58,555 | 58,475 | 58,592 | 58,521 |

The impact of technology level drivers of fusion is investigated as a means of econometrical analyses: the corresponding results are shown in Table 8. The models test the likelihood for a pair of technology fields (identified by the 4-digit IPC subclasses), to be associated simultaneously for the first time to an EPO filing: the event is interpreted as the generation of a new technology fusion. Parametric survival models with exponential distribution are applied to account for the fact that non-merging pairs may converge to a fusion in the future (a new fusion is a failure event). The selected models converge and report the highest value of the Akaike Information Criterion among diverse distributions of the survival models (Weibull, gamma, loglogistic and lognormal). Table 7 shows the hazard rates: values higher than one are positive coefficients, lower values are negative. The models are estimated by adding the variables stepwise in order to test the robustness of the results. All models include dummies to control for time and sector specificities.

The stock level of crossed backward citations between each of the two merging fields (CONVERG_LVL) is significantly and positively correlated to the generation of new fusions; this suggests that the fusion event is generally anticipated by an overlap process in which the future combining technology fields cite one another: the greater the number of mutual citations, the higher the probability that a new invention incorporates both of them and generates a new fusion. The results for technology cycle (TECH_CYCLE) are not robust and do not seem to have a significant impact.

With the exception of technology scope, the coefficients of the variables describing average complexity of the inventions in the merging fields have negative signs. Complexity, measured in terms of average number of backward patent and non-patent citations (BWD_CIT and SCIENCE) and number of inventors, is negatively correlated to the probability of emergence of a new fusion: hybridized fields are characterized by a relatively lower number of citations and a relatively smaller team of inventors. In contrast, fields with wider technological scope (TECH_SCOPE) are, as expected, more likely to result in inventions encompassing both technical areas.

The average technical value of the examined pairs of technologies (FWD_CIT) shows no significant differences if they culminate in a new fusion or do not merge during the examined time frame. In fact, geographical scope (GEO_SCOPE) shows a reducing factor.

The results are robust to inclusion or exclusion of the variable SCIENCE; however they should be interpreted with caution as discussed in Meyer (2000a, 2000b). Controls for the number of patents filed and technological distance have the opposite signs. The results for technological distance, unlike the preliminary comparison between fused and non-fused pairs, would suggest that more proximate technologies are more likely to merge ceteris paribus, although this result is not robust across models. The size of the technological domain measured as stock of filed patents (SIZE) indicates that new fusions are more likely in larger fields with more patents.

## 5. Discussion

The analysis in this paper exploits the availability and characteristics of patent data which commonly are employed to proxy for certain technological dimensions and the associated hierarchical classification of the inventions, the IPC code which provides a structure useful to identify technological fields and their overlap across time. The analyzed sample includes all EPO patents filed between 1991 and 2007.

This study identified the yearly generation of new technology fusions measured as occurring when two 4-digit IPC subclasses are associated to a patent for the first time. The analysis ascertained the emergence of new fusions as 12.8% of the potential pairs available at the beginning of the period. A measure of the degree of convergence process, that is, the stretching of one field towards another, has been defined by considering the stock of cross citations between two fields. Almost all of the new fusions identified show the presence of cross-citations before the focal merge. Although the evidence would seem to support the presence of a correlation between the convergence process and the final fusion of the two fields considered, note that 58.5% of the potential pairs of fields that did not merge during the time frame of the study, also show patterns of convergence. For this reason, a comprehensive multivariate econometric analyses was performed.

Preliminary statistics on the data collected and treated at the level of technological area show that “Mechanical engineering” accounts for more than 50% of the fusions while “Instruments” accounts for the smallest number. At a finer level of analysis, “Measuring” is the most frequent 3-digit IPC class, suggesting that the high share for “Mechanical engineering” might be due to the co-occurrence of many subfields while the technical field “Measuring”, part of the area “Instruments”, is involved in a relatively larger number of fusions. The industry level analysis provides evidence of the robustness of the approach to the identification of new fusions among those sectors where patent protection is relevant and extensive since several of the industries cited in the literature as exemplar are identified as the most frequent by the proposed methodology.

### 5.1. Theoretical implications

With respect to scientific literature, the econometric multivariate analysis shows that some of the characteristics of the potentially combining fields are significantly related to the emergence of a new fusion. A relatively higher level of linkages in terms of cross citations between technical fields is more likely to be found within a new fusion. The finding empirically supports previous literature that suggests that fusions can be considered the result of a convergence process when different fields “stretch out to one another” (Hacklin, 2007; Curran, 2013). Technology cycle and absorption speed do not seem to affect the likelihood of identifying a new fusion. Contrary to expectations, the evidence suggests that fields characterized by lower levels of technological complexity (in terms of backward citations, science basicness and inventor team size) are more likely to merge. In particular, new fusions occur more frequently among fields less grounded in scientific research, and focused more on applied research; this finding calls for more research since previous literature (e.g. Karvonen and Kässi, 2013; Hacklin, 2007) suggests that more basic research fields are more likely to converge. The smaller average size of the inventor team might be related to the higher presence of small firms and individual inventors which generally are more able to combine different technologies, while larger teams might be more likely to be involved in dedicated projects in larger companies and field-specific research centers. This finding is balanced by the result for collaborativeness: in line with theorized expectations (Curran, 2013), fields that produce new fusions are characterized by a relatively higher number of patent applicants, a proxy for collaborations.

The results suggest that the emergence of a new fusion is a response to specific needs in fields in the later stages of their technological trajectories, for example, after the inflection point along the S curve, and characterized by a relatively lower degree of complexity.

It is interesting that there seems not to be a significant difference in field-level technical merit and that new fusions occur more often if the overlapping fields are relatively more geographically focused. One reason for this might be the initial lower propensity to invest in several patent applications to multiple jurisdictions, in order to limit the patenting fees for inventions with more uncertain market results. Alternatively, the protection provided in a limited set of countries might be sufficient to guarantee wider coverage. For example, inventions embedding diverse fields for the first time might be harder to replicate, mostly for firm collaboration or asset related rather than technical reasons, based on the technological complexity.

### 5.2. Managerial and policy implications

The evidence provided by this study has implications for managers and policymakers in particular, by considering the potential predictive power of some of the characteristics of the merging fields: although a complex process, studying the interdependencies across technologies might help firms to predict change and future needs (Jeong and Kim, 1997; Choi et al., 2007;

Karvonen and Kässi, 2013). Managers might benefit from an improved understanding of the convergence process since, as Hacklin (2007) notes, the translation of knowledge bases into technologies is the result of an autonomous process rather than a conscious managerial action. The information on emerging overlapping trends derived from patent data could help managers to exploit new opportunities, avoid threats, plan future R&D, and forecast technological trends in the transformation of industries (Choi et al., 2007; Kim and Kim, 2012; Hacklin et al., 2013; Karvonen and Kässi, 2013). From a broader perspective, understanding technology fusion dynamics might help in the definition of science and technology policies by comparing investments and other forms of support in single domains with those in interdisciplinary areas (Nemet and Johnson, 2012).

### 5.3. Limitations and future research

This study has some limitations, especially in relation the methodological approach adopted. First, the sample is limited to the EPO patents, and although infrequent, it is possible that some of the considered "new" fusions occurred before 1991. Future research could extend the study time frame and the number of jurisdictions (e.g., by including the US Patent and Trademark Office). There is also a limitation related to the choice of the IPC hierarchical structure which completely defines the technology fields; this could be considered a shortcoming since the analysis of different levels of technological systems could yield new insights into their evolution and a more comprehensive view of their structure, as noted in Roepke and Moehrle (2013). Hence, comparison of the results from analyses carried out at different levels of hierarchical classification might provide interesting findings. The approach is limited also by the assumption that all technology fields can combine with one another while some classes might be mutually exclusive. This might be the case of residual classes referring to "subject matter not otherwise provided for" in each technology cluster (A99Z, B99Z, etc. and also subclasses like B25F, F23M, etc.). Furthermore, consideration should be given to combinations of two and also three or more fields. There is a potential issue associated to the origin of the IPC subclasses, whether they are provided by the applicant or assigned by the examiner: although preliminary evidence based on manual sampling does not seem to support a potential incremental effect induced by patent examiners, the hypothesis should be explored further. Finally, the impact of previous linkages defined through backward citations might be worth further investigation.

Future research could focus also on understanding the technological trajectories of fully merged technological fields, by comparing their trend and characteristics with spot fusions and with single-coded technical fields. An interesting direction for research might be to focus on the identity of the owners of the fused technologies, whether they are large or small firms, research centers or individual inventors.

## 6. Conclusions

The aim of this study is to provide empirical support for the findings of previous literature on industry convergence, with a particular emphasis on technology fusions in those sectors which protect their innovations by patenting. Previous empirical analyses do not focus on the technological dimensions but rather on the firm- or sector-level characteristics or on a specific technical field. The lack of data limits the analysis of technology fusion (No and Park, 2010; Kim and Kim, 2012) and requires further empirical tests with a broader wider approach to provide complementary evidence and extend research at the technology level. This work proposes a methodological approach to operationalize the identification of both technology fusions and converging processes (according to Curran's definition – Curran, 2013) relying on patent data. The proposed method allows the identification of the birth of new technology fusions and also to investigate the technology-level characteristics that are correlated to such instances.

The analysis of all the EPO patents between 1991 and 2007 identified a significant amount of new fusions, especially in those industries cited in the literature as exemplar, supporting the robustness of the proposed methodological approach. The investigation on the drivers of merged technologies suggests that the birth of a new fusion is more likely to occur in fields in the later stages of their technological trajectories, with a relatively lower degree of complexity, focused more on applied research, and with a narrower geographical scope of patent protection. These results contribute to a further understanding of the dynamics of technological trajectories, in particular when considering the higher value associated with interdisciplinary research and cross-industry innovation. More specifically, the analysis of the interdependencies across technologies derived from patent data might help firm managers and policymakers to anticipate the transformation of industries and the emergence of new fusions, to improve the allocation of investments and to support the definition of science and technology policies.

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