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What drives technology convergence? Exploring the influence of technological and resource allocation contexts

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ABSTRACT

Although many studies emphasize the importance of technology convergence, comparatively few ask, "What drives technology convergence?". This study empirically demonstrates how technological and resource allocation contexts nourish technology convergence. We use the data from government-supported R&D projects in Korea and measure convergent patents as ones with multi-assigned R&D domains. The results show that earlier stage of technology life cycle, lower technology readiness level, longer R&D timespan, or smaller R&D budget lead to the creation of technology convergence. The results justify the policy supports for technology convergence and highlight the paradoxical relationship between the affluence of R&D resources and technology convergence.

Introduction

Following the Renaissance, scientific and technological knowledge developed within their respective domains (Roco and Bainbridge, 2002). However, as socio-economic and managerial problems grew more complex, knowledge based on a single discipline was found to be insufficient to resolve them (Brew, 2008). In addition, rapid globalization and intensified technological development

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induced research and development (R&D) entities to derive various competitive advantages in emerging industries (Curran and Leker, 2011).

In this context, strategic decisions on converging technologies and associated products can critically influence the competitiveness of both enterprises and nations (Curran and Leker, 2011). Converging technologies lay the groundwork for a wide variety of technical solutions by unlocking the potential of radically novel technological developments (Roco and Bainbridge, 2002; Kim et al., 2009; Nordmann, 2004; Wolbring, 2008). Therefore, converging technologies are expected to lead and dominate next-generation technological innovations (Athreye and Keeble, 2000), as crossing disciplinary boundaries by convergence makes it possible for researchers to develop intellectual breakthroughs (Morillo et al., 2003). This aspect of convergence can contribute to the increase in innovation capabilities of research and development (R&D) entities.

Accordingly, a number of scholars have emphasized the importance of convergence and interdisciplinary research (Stone et al., 2009); R&D managers and researchers also strongly perceive its importance.[1] Since the 1980s, a certain number of corporate strategic plans have involved considerations of convergence (Lind, 2004; Bröring et al., 2006), and more than 80% of surveyed Spanish researchers have used knowledge and techniques from other techno-scientific domains (Sanz-Menéndez et al., 2001). Furthermore, more than half the knowledge in academic journals is of an interdisciplinary nature (Morillo et al., 2003).

In fact, perceiving the importance of opportunities arising from convergence, developed countries' governments have established initiatives to promote such convergence, especially in technology. For example, the National Science Foundation (NSF) in the United States has shown noteworthy interest in the convergence of nano-, bio-, information, and cognitive (NBIC) technologies (Roco and Bainbridge, 2002) and is taking action to facilitate such endeavors (Wolbring, 2008). Likewise, the European Commission has executed similar policies vis-à-vis technology convergence (Nordmann, 2004). Policymakers in South Korea and Japan have initiated plans analogous with those in the United States and the European Union (Kim et al., 2009).

However, it has not been fully clarified in what contexts R&D entities combine knowledge from different fields or what conditions promote technology convergence. By and large, technological and demand uncertainties are theoretically speculated as the determinant of technology convergence (Bores et al., 2003). More specifically, taking a heuristic approach (Llerena and Meyer-Krahmer, 2003; Bainbridge, 2006), researchers elucidate the social barriers to mingling among the R&D entities of different techno-scientific domains (Stokols et al., 2008). Conspicuously, some empirical research demonstrates a propensity on the part of individual researchers to participate in interdisciplinary research (Carayol and Thi, 2005) and investigates the correlation between the structures of convergence in R&D and standardization (Gauch and Blind, 2014). However, few studies empirically demonstrate what drives technology convergence.

This study demonstrates the influences of technological and resource allocation contexts on technology convergence among distinct macro-level techno-scientific domains. While the efficacy of programs that encourage technology convergence is in serious doubt (Metzger and Zare, 1999), identifying in what contexts convergence occurs and investigating its facilitation may broaden our understanding of convergence, perhaps helping form policy and managerial decisions in ways conducive to fostering technology convergence. Moreover, since technology convergence is a key driver of market/industry convergence (Hacklin, 2008), the deepened understanding created by this study may help us envision the forthcoming future of convergence in commercial markets and industrial activities.

This study makes distinctive contributions. It offers novel empirical evidence of the influences of technological and resource allocation contexts on convergence. Thus far, because of difficulty obtaining relevant preference data (Hacklin, 2008), previous empirical studies focus on identification of convergence and trend-watch in particular concentrating on industry convergence (Curran et al., 2010; Curran and Leker, 2011; Karvonen and Kässi, 2013; Preschitschek et al., 2012). However, while they do not empirically demonstrate hypotheses on the drivers of convergence, surveys show the

[1] Although "interdisciplinary research/interdisciplinarity" and "convergence" are both phenomena in which heterogeneous knowledge or fields are combined, they are only roughly synonymous. We review the differences between the two in Section "Definition of "technology convergence"".

importance and evidence of differentiated strategies for convergence by technological and resource conditions (Bröring et al., 2006; Preschitschek et al., 2011). As a first step to understanding the drivers of this understudied area of convergence, our study provides further research on technology convergence, primarily exploring theoretical and empirical concerns. Furthermore, based on reliable and complete enumeration data, this study presents the characteristics of R&D activities as key contexts for technology convergence. Although technology changes derive from R&D entities' investment decisions (Katz, 1996) and from technological characteristics (Roco and Bainbridge, 2002; Bainbridge, 2006), the bibliographic data commonly used in similar science convergence studies cannot link the characteristics of R&D activities with the knowledge derived from them. Survey data could mitigate this weakness, but such data might have other serious weaknesses of reliability and generalizability. For example, previous research on interdisciplinary research has tended to employ survey data from a single institute, focusing on a brief time-period (Carayol and Thi, 2005). We use data on patents derived from government-sponsored R&D programs covering a nine-year period; the data include standardized characteristics of technology and associated R&D projects. Thus, this study provides a profound understanding of the beginning of technology convergence using reliable and generalizable evidence.

The remainder of this study is organized as follows. Section "Theoretical background and hypotheses" briefly discusses the definition of "technology convergence," introduces the heuristic framework of convergence among techno-scientific domains, and provides the formulated hypotheses. The data and empirical methodology are described in Section "Data and methods". The results are discussed in Section "Results", and concluding remarks are offered in Section "Discussion and conclusions".

Theoretical background and hypotheses

Definition of "technology convergence"

Although convergence is a much-discussed topic and has notable economic implications (Katz, 1996), the term itself functions as a buzzword (Curran and Leker, 2011) based on its multifaceted application to science and technology (Nordmann, 2004).[2] In particular, technology convergence is often misunderstood as a synonym of technology fusion. In general, technology fusion denotes the creation of a sub-segment in the same area as parts of the original segment (i.e., mere combination), whereas convergence describes the concept of discrete items moving toward unity or uniformity or the merging of distinct technologies, devices, or industries into a unified whole (Curran and Leker, 2011; Phillips, 2001). The primary distinguishing feature of convergence is that it specifically denotes conflation between previously distinct knowledge, technology, product, or industry domains. Therefore, convergence, in a strict sense, differs from "fusion" (Phillips, 2001; Kodama, 1992). For example, convergence between telephony and radio communication technology developed into telecommunication technology, which eventually created the personal cellular market (Phillips, 2001). Interdisciplinarity,[3] meanwhile, only characterizes integration at the discipline level (Kodama, 1992; Wagner et al., 2011); interdisciplinary research (or interdisciplinarity) is understood as science convergence in a broad sense (Curran and Leker, 2011).

By and large, convergence can be categorized as (i) science convergence that merges different scientific disciplines or areas, (ii) technology convergence that combines technologies of different application areas, and (iii) industry convergence that unites sets of companies with different technology bases, application fields, and target groups in various markets (Curran and Leker, 2011). In the advent of each stage of convergence, the prior stages of convergence work as triggers of the convergence (Curran et al., 2010). The triggers such as scientific findings and technological developments that are nurtured each in science convergence and technology convergence can improve the pure ability of the entry that owns them to apply them to product or process related to convergence, because technology convergence creates a new function through the integration of

[2] For instance, Gambardella and Torrisi (1998) employee "technological convergence" as an opposite concept of technological diversification in R&D activities, a term interpreted at the technological portfolio level.

[3] The boundary of interdisciplinarity is also unclear because multidisciplinarity and transdisciplinarity are also similar concepts. Several scholars have compared and refined the terms (Wagner et al., 2011).

different technological elements (Kodama, 1995). As in the emergence of innovation (Mowery and Rosenberg, 1979), such improvement on the supply-side and change on the demand-side such as changes in customer structures and behaviors, which prefer satisfying multiple needs with one transaction, lead to industry convergence (Curran et al., 2010; Katz, 1996). In this process, total substitution of previous technological/industrial sectors pushes R&D entities to keep up with trends of convergence (Curran et al., 2010), demanding for a strategic approach to convergence.

Thus, as one of the triggers of industry convergence and sources of technological competency, technology convergence has received substantial attention although little of the actual process in technology convergence is known or has been empirically demonstrated. Furthermore, technology codified as patents is a minimal scope for R&D program management and represents a major output manifestation; thus, there is little doubt that convergence management at the technology level is necessary for governments and firms.

Context of technology convergence

The contexts of convergence have been discussed from diverse perspectives, as the underlying activity (i.e., R&D) of convergence is performed in various contexts. For that reason, scholars have paid considerable attention to technological factors, institutional obstacles, and structural aspects such as assessment and funding problems, believing that these together affect the willingness to promote convergence and determine its success (Stokols et al., 2008; Klein, 1996).

Incorporating the aforementioned factors and concerns, we design a short technology development process consisting of input, development, and output, as shown in Fig. 1. We review each of these in the following sections. Simply put, R&D entities utilize their own resources to develop new technology. First, we deal with the resources for R&D projects as the main input. Resources as inputs bear outputs, and R&D projects typify the formal resource basis of R&D activities. Therefore, their performance is the key element on which governing bodies of R&D entities base assessment. This

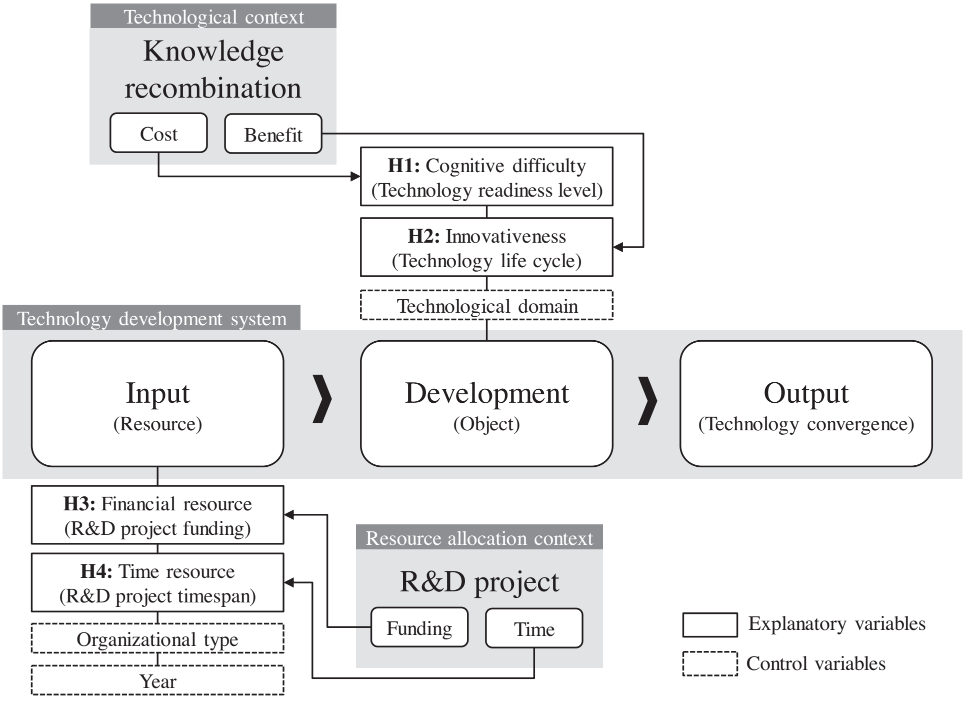

Fig. 1. Theoretical framework for the development of technology convergence.

resource allocation context, especially for primary resources (i.e., funding and time), thus potentially affects the manner in which R&D entities pursue technology convergence. These resources and other input controls (i.e., organizational type and year) are considered input factors in our system. The next step in our system, development, occurs in the technological context in which R&D entities encounter technological difficulties and opportunities while exploring new technological objects. The process of recombination of distinct areas of knowledge, which is a feature of technology convergence, has been theorized to create certain costs and benefits. Our study specifies each of these conflicting factors as a primary concern of technology convergence (i.e., cognitive difficulty and innovativeness) under technological control (i.e., technological domains).

Technological context

Scholars investigating the development and structure of technology (Arthur, 2009) have found that a single, emerging technology does not evolve in isolation but results from intensive networking and recombination among different areas. Such recombination among different domains creates benefits in the form of the discovery of novel and innovative solutions. Concurrently, however, it can be mired in several problems: distinct communication codes and languages, different discipline-specific theories and methods, and the costs of overcoming such cognitive differences (Llerena and Meyer-Krahmer, 2003). Such problems eventually increase the potential transaction costs in developing convergence (Nordmann, 2004).

The benefits of recombining information across different techno-scientific domains increase at a decreasing rate with the distance between those domains,[4] whereas the costs thereof increase at an increasing rate with such distance (Llerena and Meyer-Krahmer, 2003). This is based on the assumption that larger technological distances produce potentially fruitful outputs, more difficult communication problems, mutual complementarities, and cross-fertilization. In addition, by suggesting an analytical framework that consists of bimodal factors (i.e., costs and benefits) the authors imply that R&D entities are reluctant to be involved in technology convergence when potential costs exceed potential benefits. This framework explains why most R&D entities rarely develop converging technologies or interdisciplinary knowledge across macro-level discipline boundaries. When the distance between domains is short, the costs associated with the inherent difficulties are likely less significant than the benefits that technology convergence development derives; on the other hand, when the distance between domains is great, the costs are likely to exceed the benefits (Llerena and Meyer-Krahmer, 2003).

The more important point is that the functions of the costs and benefits vary by context (Llerena and Meyer-Krahmer, 2003). One notable context is the technology readiness level, which primarily indicates how close an R&D output is to being operational (Jeong et al., 2011). When R&D is at the stage of making a technology operational rather than strategically developing new ideas, the transaction costs for recombining knowledge increase (Brousseau, 1993). Technology development at a higher readiness level—i.e., further from basic and fundamental research—requires more control in the determination of visible outputs such as intellectual property. In addition, the potential degree of technological complexity and diversity at this level is certainly higher than at lower levels (Jeong et al., 2011). In fact, due to the relatively high transaction costs inherent in intense networking at a high level of technology readiness, researchers at this level tend not to collaborate with other knowledge providers—even those within the same organization (Jeong et al., 2011). Citing the case study of manufacturers of medical lasers (Schmoch et al., 1996), Llerena and Meyer-Krahmer (2003) also examine this proposition, claiming that convergence among distant domains primarily occurs at the basic research level. Hence, technology convergence is more likely to occur when the technology readiness level of the R&D output is low.

Hypothesis 1. The lower level of technology readiness, the higher probability of technology convergence

Another notable technological context involves the technology lifecycle. By describing the lifecycle patterns of technologies as similar to the biological cycles of living beings, this concept illustrates

[4] Therefore, the benefits follow an inverted-U shape as the technological distance increases.

technological evolution based on the theory of diffusion (Mansfield, 1961) and the adoption of innovation (Ansoff, 1984).

In this respect, it can be understood that the relative opportunities potentially afforded by technology convergence vary by the developmental phase of the technology lifecycle because of differences in ''innovativeness'' between converging technologies and ordinary technologies (Nieto, 1998). In an early stage of the technology lifecycle, the rate of growth depends on newness, which is one of the major benefits of atypical knowledge combination: technological newness and novelty define the speed of growth for both the technology itself and its associated products (Betz, 1993). As a form of technology innovation, convergence opens up possible new ways of coping with new things (Katz, 1996); thus, technology convergence at an earlier stage in the technology lifecycle can induce R&D entities to undertake R&D activities by providing relatively larger incentives. On the other hand, the impact of innovativeness in late stages of the technology lifecycle is not sufficient to improve technology performance and the sale of related products (Nieto, 1998).

We can thus surmise that R&D activities related to various stages of the technology lifecycle follow the benefits curve illustrated in Llerena and Meyer-Krahmer's analytic framework (Llerena and Meyer-Krahmer, 2003). Hence, we can hypothesize that the occurrence of technology convergence has a negative relationship with the stage of the technology lifecycle.

Hypothesis 2. The earlier stage of the technology lifecycle, the higher probability of technology convergence

R&D resource allocation context

R&D funding management is considered an important policy tool because such financial support contributes to increased R&D outputs (Breschi and Malerba, 2011). Funding also influences the qualitative facets of R&D activities. Previous studies have commonly shown that the scale of funding has a positive relationship to the impact of research (Gonzalez-Brambila and Veloso, 2007).

In this respect, we can surmise that potentially high impact can increase the probability of technology convergence taking place—which, as discussed, in turn implies the advent of technology covering heterogeneous techno-scientific domains. Since the impact of research is defined as its actual influence on research activities within the vicinity of the techno-scientific domain (Moed et al., 1985), R&D outputs with higher impact can extend to a broader area. That is, higher-impact technology has a greater possibility of being referenced and applied to other domains.

The perspective of practical R&D activity decisively supports the positive effect of the scale of funding on the advent of technology convergence. The financial scale eventually determines the R&D scope (Sargent, 2004), thus also potentially increasing the likelihood that the domain of technology will overlay diverse fields. It can also enhance the ability to enlist researchers, so that the R&D entity's increased human capital—i.e., the sum of the scientific, technical, and social knowledge embodied in a workgroup (Bozeman et al., 2001)—can help discern opportunities to merge heterogeneous technologies.

Hence, we can surmise as follows.

Hypothesis 3. The larger scale of an R&D project's funding, the higher probability of technology convergence

Another issue of concern for R&D resource allocation is the timespan of R&D funding. Governments may wish to make the R&D process more efficient by accelerating the speed of R&D (shortening the R&D period) but maintaining the same research goal.[5] However, in terms of practical R&D execution, it has been prevalently argued that a short R&D project time period can deter researchers from undertaking in-depth activities related to knowledge production or networking, inducing them to focus primarily on easily predicted consequences. Short funding timespans create anxiety for researchers, pushing them to generate the expected results needed to secure further funding (Gulbrandsen and Smeby, 2005).

[5] For example, in 2009, the Ministry of Knowledge Economy in South Korea executed a plan to speed up R&D activities by shortening the scheduled period of government-supported R&D programs to lower the impact of the global financial crisis.

For this reason, researchers tend to desire both abundant and long-term funding when searching for innovative solutions and discoveries through convergence. In fact, convergence-related R&D is considered more risky and thought to require a longer timespan (Schmoch et al., 1994), so it is heuristically sensible that during a longer R&D activity period, more diverse methodologies and perspectives can be applied to the development of technological solutions. Hence, we can surmise as follows.

Hypothesis 4. The longer timespan of an R&D project that creates technology, the higher probability of technology convergence

Data and methods

Data sources

We employ data from the National Science and Technology Information Service (NTIS) that contains information about the features of wholly government-supported R&D programs and their outputs in South Korea. Researchers who undertake any government-supported R&D project are intended to register their R&D outputs, such as patents, as outputs of R&D activities.

The use of this novel database featuring a broad time period and technology domains makes it possible for us to reveal the generalized behaviors of R&D entities vis-à-vis technology convergence—especially by R&D entities that use public R&D resources. As of 2010, a total of 66,244 patents in South Korea had resulted from government-supported R&D projects that NTIS managed. Some of the patents do not include sufficient information to be included in this research, including that pertaining to the macro-technology domain, the stage in the technology lifecycle, the type of R&D entity, and the identification code of the associated project. After excluding those patents, we have 51,837 patents to use in this study, with a timespan of patent applications extending from 2001 to 2009, inclusive. Some patents have not yet been approved for registration by the Korean Intellectual Property Office (KIPO), but it is sensible to understand them as the results of R&D activities that are still under review in the registration process; therefore, we include all patents regardless of the existence of a registration number.

Measurements of technology convergence

To measure technology convergence indicators, we need to review the means of measuring those in science convergence, given the dearth of empirical studies on convergence at a technological level. Although scholars have disagreed about which indicators are most appropriate to measure interdisciplinarity (Morillo et al., 2003), they have generally demonstrated the structure of science convergence through bibliometric methods. Several studies have analyzed interconnectivity among disciplines using cross-disciplinary citation among journal articles (Porter and Rafols, 2009; Porter et al., 2007; Small, 1999; van Leeuwen and Tijssen, 2000), the co-classification of journals' subfields (Morillo et al., 2003; Tijssen, 1992), or co-wording among journal articles (Palmer, 1999). In particular, having the same foci as this study, several science convergence studies (Porter and Rafols, 2009) focus on interdisciplinarity among macro-level disciplines using citation analysis of journals in the six macro-level research domains. Similarly, based on the multi-assignation of journals to macro-level subject categories, some studies posit the importance of macro-level science convergence analysis and find that the propensity of convergence varies by macro-level research domain (Morillo et al., 2003).

However, such bibliometric methods cannot be applied to technology convergence studies because academic journals cannot represent technical/commercial knowledge and innovative activity. Given the difference, industry convergence studies use similar methods but different measures. The most representative of which are seen is the works of Curran and Leker (2009, 2011) and Curran et al. (2010), who define and refine the methodology based on co-classifications of international patent classification (IPC) and match with industrial categories. Karvonen and Kässi (2013), which explore the evidence of convergence through patent citation, are also based on IPC as well as matching it with industrial categories.

Hence, we use an alternative means of measuring technology convergence based on the multi-assignation of patent documents. Admittedly, patents do not measure all relevant knowledge held by an R&D entity, because knowledge can take such diverse forms as academic papers, patents, copyright, reports, and undocumented knowhow. However, patent documents constitute an ample information source that describes and represents technological innovation (Ernst, 2003), on which this study primarily focuses. The majority of previous research has employed patents as an indicator of technological innovation and the specific strengths of R&D entities (Lee and Kim, 2012); following this trend, we also use patents as an indicator of technological innovation.

Another underlying issue in the identification of technology convergence is the classification of technology domain. Practically, one can say classifications of technology domain already exist in various forms, including the IPC or the National Science and Technology Standard Taxonomic System.[6] However, to derive better practical implications, a taxonomic framework should consider the standpoint of governmental policy aimed at technology convergence; thus, we briefly review the typologies of technology that major governmental bodies define for technology convergence.

According to the government initiatives of major developed countries, technologies can be categorized into discrete domains. The NSF in the United States proclaims four major technology convergence domains: nanotechnology (NT), biotechnology (BT), information technology (IT), and cognitive science (CS) (Roco and Bainbridge, 2002). The European Commission defines a similar typology (NT, BT, IT, social science, and humanities) (Nordmann, 2004), as does the Japanese government in the Third Science and Technology Basic Plan (NT, BT, IT, and environment technology [ET]) (Kim et al., 2009). In the case of South Korea, the Office of Science and Technology Innovation also proclaim Promising New Future Technologies (6T), consisting of the six major technology domains for convergence: NT, BT, IT, ET, space technology (ST), and culture technology (CT)[7]; all R&D projects are classified per those domains (Oh et al., 2010).[8]

In understanding these typologies—which contain macro-technology categories whose definitions vary by country but nonetheless show similarities—numerous experts have actually designed and introduced substantialized or substantializable cases of technology convergence among macro-technology domains (Roco and Bainbridge, 2002). In addition, the South Korean typology for technology convergence is widespread within South Korea and has been used in planning practical technology convergence strategies as well as processes of planning, investing in, and assessing national R&D programs (Kim et al., 2009). Thus, it is sensible to make typology a fundamental framework in analyzing technology convergence—at least in the South Korean context.

The key measurement issue is how to define the original source of technological knowledge. A sensible way of defining the base level of multi-assignation is to set sourced R&D activities (e.g., conducting R&D projects) as the sources of techno-scientific domains under the premise that technological knowledge derives from R&D activities. Regardless of the different paths that eventually lead to technological emergence, an upsurge of technology accompanies a set of linked knowledge (Llerena and Meyer-Krahmer, 2003). In fact, some scholars argue that convergence can also be gauged in terms of proposals or projects (Porter et al., 2007).

As illustrated in Fig. 2, R&D activities bear technologies (e.g., patents) as outputs. Under the premise that R&D projects are a key proxy for the R&D activities within them aimed at producing technological outputs, the multi-assignation of sourced R&D projects for patents provides evidence of whether the produced technologies are convergent. At the time of planning R&D projects, researchers declare the macro-technology domain in which R&D projects are based and then submit the proposal to funding agencies. If accepted, they undertake those projects. During or after the R&D activities, they register the produced patents along with information on what projects contributed to the creation of the patents. Because of legal issues related to the ownership of patents and the distribution of profits—such as licensing fees that result from the patents—researchers are careful to refer to the contributing

[6] The standard taxonomic system for science and technology in South Korea.

[7] Unlike other technology domains, CT has an uncommon definition rarely used in other nations: technology for cultural contents such as virtual reality, cyber-communication, and multimedia content.

[8] Projects that do not belong to any of the six domains are categorized as ETC.

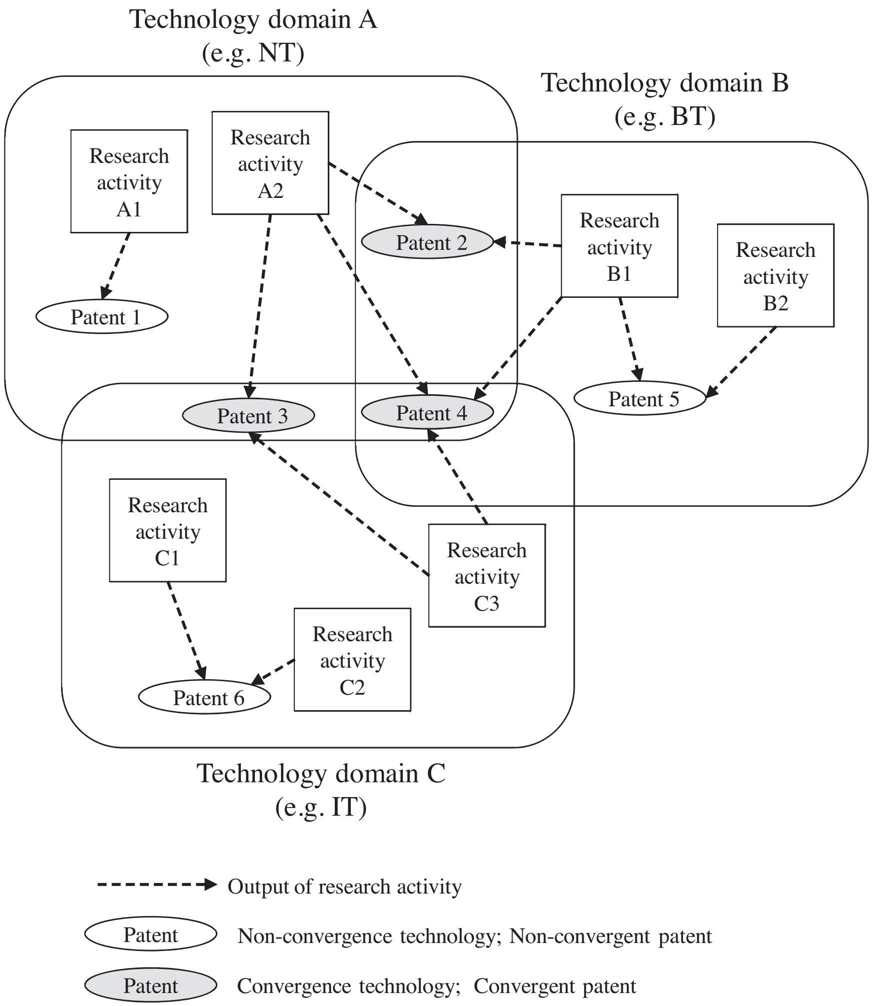

Fig. 2. Framework for defining convergent technology.

R&D projects using ratios that indicate how much the projects contributed to the patents when reporting the patents created.

While some patents have a multi-assignation of sourced R&D projects with homogeneous macro-technology domains (e.g., Patents 5 and 6 in Fig. 2) or only a single assignation (e.g., Patent 1 in Fig. 2), some other patents have multi-assignations of the sourced R&D projects with heterogeneous macro-technology domains (e.g., Patents 2–4 in Fig. 2). We presume that the latter type of multi-assignation represents technology convergence, since such a type reveals that the researchers have referred to and blended technological knowledge from heterogeneous technology domains; hereafter, we define such patents as "converging patents." For example, Patent 5 in Fig. 2 is the output of both Research activity B1 and B2, which are included in the Technology domain B. According to our definition, therefore, Patent 5 is not a "converging patent" even if this patent stems from multi-assignation of sourced R&D projects. Contrariwise, Patent 2 in Fig. 2 is produced at the same time from Research activity A2 and B1, and each Research activity is included in the Technology domain A and B respectively. Thus, Patent 2 is a "converging patent" because of multi-assignation of the sourced R&D projects with heterogeneous macro-technology domain.

Methodology and variables

In order to understand the factors affecting the converging technology development, we empirically analyze the influences of different variables based on our hypotheses on the creation of converging patents. In the empirical analysis below, y_i^* is a latent variable and determined by the model as shown in Eq (1):

$$y_i^* = x_i'\beta + u_i \quad \text{where} \quad y_i = \begin{cases} 1 & \text{if } y_i^* > 0 \\ 0 & \text{if } y_i^* \leq 0 \end{cases} \tag{1}$$

In this formulation, $x_i'\beta$ is called the index function (Greene, 2003).

While y_i^* is not observed, the observations y_i for the analysis are patents as outcomes of national R&D programs and each observation represents a patent. By using the technological taxonomy and the multi-assignation method reviewed in Section "Measurements of technology convergence", each observation is shown in two states, which equals 1 if the patent is a converging patent and 0 otherwise. That is to say, a dependent variable (i.e., *Convergence*) of our analysis takes only two values that are denoted by 0 and 1. When we assume that the error term (u_i) follows a standard normal distribution, we use the probit model (Greene, 2003; Maddala, 1983).[9]

In Eq. (1), x_i represents the independent variables that affect the probability of creating converging patents. As an independent variable, *Tech_RD_Level* indicates the technology readiness level; it is obtained from the registered features of the relevant R&D projects. The Organization for Economic Co-operation and Development (OECD) categorizes the types of government-supported R&D programs into basic research, applied research, and experimental development (OECD, 2002) The NTIS mandates that researchers report their R&D project type based on the OECD's typology when registering projects. Like previous studies (Jeong et al., 2011), we presume the continuous technology innovation model and code this variable as a linearly increasing value by level, i.e., 1: "basic research," 2: "applied research," and 3: "experimental development." In cases of multi-assignation patents, we adopt the technology readiness level of the R&D project whose contribution ratio is the highest among all R&D projects related to with the patent as a proxy for the characteristics of the sourced R&D projects.

Tech_Life_Cycle indicates the phase of the technology lifecycle; it is obtained in the same way as *Tech_RD_Level*. Previous studies specify the technology lifecycle by level of maturity: embryonic, growth, mature, and aging (Roussel et al., 1991). Consistent with the specification of previous study (Roussel et al., 1991), *Tech_Life_Cycle* is coded as a linearly increasing value by the phase, i.e., 1: "embryonic," 2: "growth," 3: "mature," and 4: "aging"; in the case of multi-assignation, the same rule as in *Tech_RD_Level* is applied.

RND_Budget represents the annual average amount of funding, in the logarithmic scale number of millions of KRW, for the R&D projects to which the patent is attributed.[10] To nullify the effect of inflation, we employ deflated annual budget values for R&D projects. The use of annual R&D budgets makes it possible for us to discern the actual impact of financial support, since the entire R&D budget of a project is certainly proportional to the timespan of the R&D project. Furthermore, to reflect the actual contribution of resources on the creation of multi-assignation patents, the weighted average of the annual average amount of funding based on the contribution ratio of R&D projects is used for *RND_Budget*.

RND_Period is the duration, in years, of funding for the R&D projects to which the patent is attributed. This variable is measured with the same rule used for the weighted average in *RND_Budget*.

We introduce the macro-technology domains for controls. Neither convergence nor technology innovation occurs uniformly across all techno-scientific domains; in addition, not every domain is conducive to convergence. Therefore, as in the discussion in Section "Measurements of technology convergence", we set dummy variables as controls based on the 6T typology of macro-technology domains. In this respect, we assume that the technology domain whose share of contribution to a patent is highest is the technology domain of the patent; hereafter, we call this the "key technology domain." In this setting, we set the case in which technology is categorized into "et cetera" as the baseline for technological dummy variables.

[9] The probit model is estimated by STATA 12.

[10] KRW 1 million was approximately USD 884.17 as of March 2012.

We include controls for type of organization as well, since the organizational context can affect the environment for convergence (Llerena and Meyer-Krahmer, 2003). The variables indicating the organizations involved in the development of technology are exclusively designated per the following dummy variables. *Indu* indicates that the industrial sector alone developed the technology without any collaboration with a university or government research institute. Accordingly, *Indu* takes a value of 1 if only the industrial sector was involved in developing the technology, and 0 otherwise. In the same way, we set *Univ* for universities and *Gov* for government research institutes. For the collaboration modes, combinations of the three sectors—i.e., *Indu–Univ*, *Univ–Gov*, and *Indu–Gov*—are created, as collaborative R&D entities can work on R&D projects with strategic motivation under difference circumstances (Miotti and Sachwald, 2003). In this setting, the collaboration case in which all types of R&D entities (i.e., university, government, and industry) work together is set as the baseline for organizational dummy variables.

Lastly, we include dummy variables for patent application year from 2002 to 2009 because convergence occurs not as mere status quo but as an evolving process that can be affected by the environmental factors of the era. For example, *Y2002* takes a value of 1 if the patent application year is 2002, and 0 otherwise. Patents assigned in 2001 work as the baseline for the time dummy variable.

Definitions of the variables are summarized in Table 1.

Table 1
Definitions of dependent and independent variables.

Variable	Description
Dependent variable	
Convergence	Dummy equal to 1 if the patent is attributed to the R&D projects that are assigned to heterogeneous macro-technology domains; if not, 0
Independent variable 1: technological context	
Tech_RD_Level	Technology-readiness level of the R&D projects that contribute to the invention of the patent (1: basic research; 2: applied research; 3: experimental development)
Tech_Life_Cycle	The phase of technology lifecycle at which the R&D projects are assigned to the patent (1: embryonic, 2: growth, 3: mature, 4: aging)
Independent variable 2: R&D resource distribution context	
RND_Budget	Weighted average of the deflated annual average funding amount for the R&D projects to which the patent is attributed, the logarithmic scale number of millions (KRW)
RND_Period	Weighted average of duration, in years, of funding for the R&D projects to which the patent is attributed
Controls	
IT	Dummy equal to 1 if the key technology domain is info-technology; if not, 0
BT	Dummy equal to 1 if the key technology domain is bio-technology; if not, 0
ST	Dummy equal to 1 if the key technology domain is space-technology; if not, 0
CT	Dummy equal to 1 if the key technology domain is culture-technology; if not, 0
NT	Dummy equal to 1 if the key technology domain is nano-technology; if not, 0
ET	Dummy equal to 1 if the key technology domain is environment-technology; if not, 0
Indu	Dummy equal to 1 if industrial sector is solely involved in developing the technology; if not, 0
Univ	Dummy equal to 1 if university sector is solely involved in developing the technology; if not, 0
Gov	Dummy equal to 1 if government research institute sector is solely involved in developing the technology; if not, 0
Indu–Univ	Dummy equal to 1 if industrial sector and university sector exclusively collaborate in developing the technology; if not, 0
Univ–Gov	Dummy equal to 1 if university sector and government research institute sector exclusively collaborate in developing the technology; if not, 0
Indu–Gov	Dummy equal to 1 if industrial sector and government research institute sector exclusively collaborate in developing the technology; if not, 0
Y2002	Dummy equal to 1 if application year of the patent is 2002; if not, 0
Y2003	Dummy equal to 1 if application year of the patent is 2003; if not, 0
Y2004	Dummy equal to 1 if application year of the patent is 2004; if not, 0
Y2005	Dummy equal to 1 if application year of the patent is 2005; if not, 0
Y2006	Dummy equal to 1 if application year of the patent is 2006; if not, 0
Y2007	Dummy equal to 1 if application year of the patent is 2007; if not, 0
Y2008	Dummy equal to 1 if application year of the patent is 2008; if not, 0
Y2009	Dummy equal to 1 if application year of the patent is 2009; if not, 0

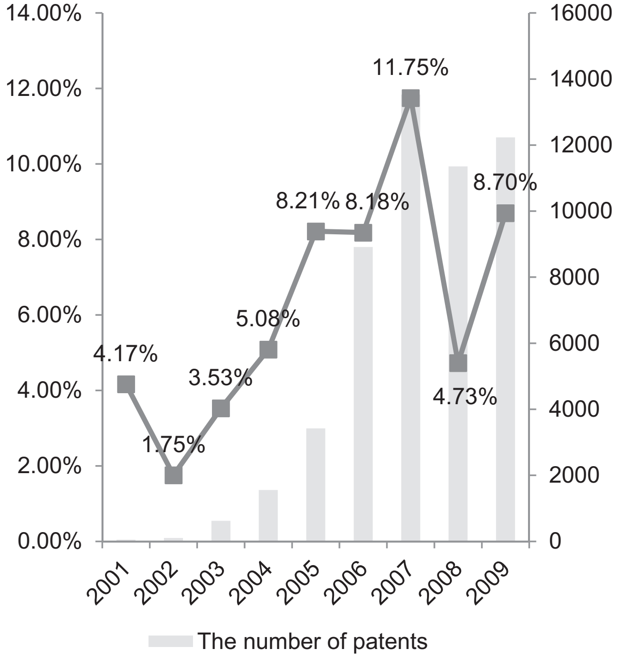

Fig. 3. Number of patents and share of convergence patents by year.

Fig. 3 depicts the number of patents and the percentage of technology convergence patents among all patents in each year. Interestingly, the ratio has ascended incrementally according to the same uprising pattern in Curran and Leker's previous study (Curran and Leker, 2011) that show for industry convergence in the chemical and pharmaceutical industries; this phenomenon indicates that the level of R&D activity corresponding to technology convergence has increased, and perhaps that the needs have also increased. The interesting point in the figure is that the trend took a downturn in 2008, during the global financial crisis—although the trend seems to have recovered in 2009. From the perspective of risk management, we can heuristically conjecture that during the economic recession period, R&D entities became less willing to be involved in technology convergence that entails greater risk, since those R&D entities—especially firms—might have been more interested in tangible future R&D outputs to reduce the financial and managerial risks inherent in R&D during a recession. However, this assertion requires further research and empirical examination.

Table 2 reports the means, standard deviations, and minimum and maximum values of the explanatory variables. Understandably, the mean of the technology readiness level exceeds 2, indicating that a majority of technologies are invented in applied research or experimental development. In addition, the mean of the technology lifecycle stage (1.784) signifies that R&D activities tend to occur in relatively early stages of the technology lifecycle.

Table 2
Descriptive statistics of explanatory variables.

Variable	Mean	Std. Dev.	Min.	Max.
Tech_RD_Level	2.318	0.757	1	3
Tech_Life_Cycle	1.784	0.684	1	4
RND_Budget	6.618	1.495	−0.048	11.923
RND_Period	2.263	1.086	1	4

Table 3
Correlations and VIF values of explanatory variables.

	(1)	(2)	(3)	(4)	VIF
(1) *Tech_RD_Level*	1				1.086
(2) *Tech_Life_Cycle*	0.261[a]	1			1.076
(3) *RND_Budget*	0.233[a]	−0.014[a]	1		1.012
(4) *RND_Period*	0.021[a]	0.006	0.008	1	1.000

[a] Significant at the 5% level.

Table 3 shows that there is no critical correlation among the explanatory variables. In addition, the variance inflation factors (VIFs), which we examined to check for the possibility of multicollinearity, turned out to be below 10, the guideline often used for such a check (Cohen et al., 2003).

Figs. 4 and 5 show the shares of technology domains and R&D organization types, respectively. Info-technology accounts for 38.3% of patents in our data, followed by miscellaneous-technology (18.8%), bio-technology (18.7%), and environment-technology (13.5%), reflecting the R&D trend between 2001 and 2009. With regard to R&D organization type, a single type of organization (i.e., *Indu*, *Univ*, and *Gov*) is seen for less than half of patents (42.2%), showing that R&D collaboration among heterogeneous organization types is more common.

Results

Table 4 shows the empirical results. To demonstrate the robustness of our estimation results, we design three specifications that have differentiated sets of respective variables. The coefficients of each variable are arranged in three individual specifications that have different sets of hypothesized contexts. Specification 1 includes the explanatory variable only as it is related to the technological context (i.e., *Tech_RD_Level* and *Tech_Life_Cycle*) and controls. Specification 2 includes the explanatory variable only as it is related to the resource allocation context (i.e., *RND_Budget* and *RND_Period*) and controls. Specification 3 includes variables related to both contexts using all independent variables. The standard errors of each coefficient are displayed in parentheses below each coefficient.

Overall, the results in Specification 1, 2, and 3 present strong consistency vis-à-vis estimated signs and significance, thus suggesting the robustness of our theoretical model for technology convergence.

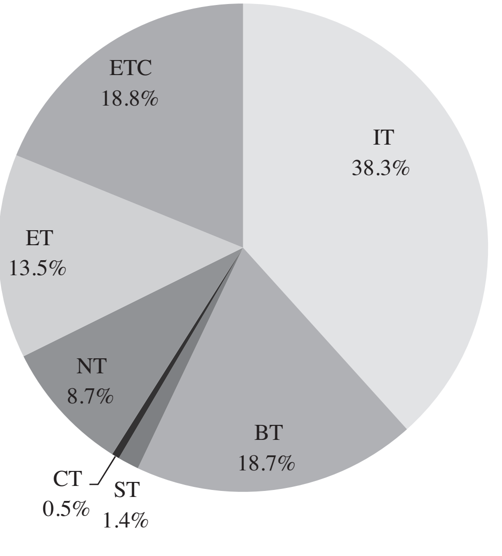

Fig. 4. Shares of technology domains among all patents.

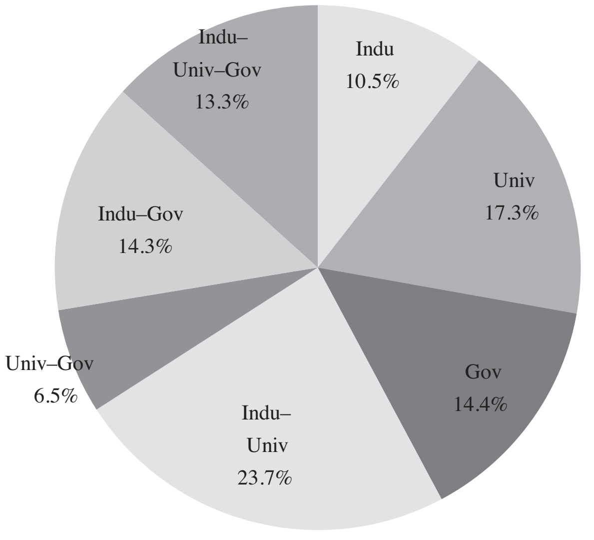

Fig. 5. Shares of organization types among patent owners.

Table 4
Probit estimations of the determinants of technology convergence.

	Specification 1	Specification 2	Specification 3
Tech_RD_Level	−0.147*** (0.013)		−0.145*** (0.013)
Tech_Life_Cycle	−0.026* (0.014)		−0.024* (0.014)
RND_Budget		−0.025*** (0.007)	−0.015** (0.007)
RND_Period		0.013* (0.008)	0.014* (0.008)
IT	−0.595*** (0.025)	−0.588*** (0.025)	−0.592*** (0.025)
BT	−0.271*** (0.026)	−0.247*** (0.026)	−0.281*** (0.026)
ST	−0.072 (0.075)	−0.070 (0.075)	−0.062 (0.076)
CT	0.237** (0.094)	0.185* (0.094)	0.230** (0.094)
NT	0.165*** (0.029)	0.213*** (0.029)	0.159*** (0.029)
ET	0.031 (0.027)	0.016 (0.027)	0.023 (0.028)
Indu	−0.389*** (0.045)	−0.476*** (0.046)	−0.412*** (0.047)
Univ	0.362*** (0.033)	0.418*** (0.034)	0.334*** (0.035)
Gov	−0.111*** (0.037)	−0.066* (0.036)	−0.121*** (0.037)
Indu–Univ	0.297*** (0.030)	0.279*** (0.032)	0.277*** (0.032)
Univ–Gov	0.410*** (0.038)	0.468*** (0.038)	0.406*** (0.038)
Indu–Gov	−0.284*** (0.042)	−0.307*** (0.042)	−0.289*** (0.042)
Year dummy	Included	Included	Included
_cons	−1.000*** (0.047)	−1.230*** (0.066)	−0.924*** (0.072)
Number of obs.	51,837	51,837	51,837
LR chi^2 (4)	3313.21	3169.88	3320.69
Prob > chi^2	0	0	0
Log likelihood	−13,186.318	−13,257.987	−13,182.581

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Regarding the estimation results, we find strong support for Hypothesis 1: the coefficients of *Tech_RD_Level* in Specification 1 and 3 are significant at the 1% level with negative signs. As *Tech_RD_Level* of R&D activities decreases, the probability of technology convergence increases: the more basic the research, the greater the probability of technology convergence being nurtured. Similarly, we find strong support for Hypothesis 2: the coefficients of *Tech_Life_Cycle* in Specification 1 and 3 are significant at the 10% level with negative signs. As *Tech_Life_Cycle* of R&D activities decrease, the probability of technology convergence increases: the earlier the phase of the technology lifecycle, the greater the probability of nurturing technology convergence.

As for the R&D resource allocation context, the results support Hypothesis 4 but not Hypothesis 3: the coefficients of *RND_Period* in Specification 2 and 3 are significant at the 10% level with positive signs. However, the coefficients of *RND_Budget* in both Specification 2 and 3 are significant at the 1% level with negative signs, which does not support Hypothesis 3. In other words, the size of an R&D budget is negatively related to the probability of generating technology convergence, while the R&D activity period is positively related to this probability.

The 6T variables illustrate the intriguing nature of technology convergence. Compared to the base group, which is miscellaneous technology (i.e., *ETC*), info-technology (i.e., *IT*) and bio-technology (i.e., *BT*) are unlikely to be involved in technology convergence, while nano-technology (i.e., *NT*) and culture-technology (i.e., *CT*) turned out to be more likely to be involved in convergence than miscellaneous technology. Accordingly, combining those results, it can be hypothetically surmised that R&D activities in nano-technology and culture-technology are more likely to create technology convergence than those in info-technology and bio-technology.

The estimations of coefficients of organizational variables show the importance of universities in technology convergence. Compared to the base group *Indu–Univ–Gov*, any variables not engaged with universities (i.e., *Indu*, *Gov*, and *Indu-Gov*) turn out to be negatively significant at the 1% level in every specification. However, a similar pattern was not found for government research institutes: *Gov* is negatively significant at the 1% level in every specification.

In summary, technology convergence is likely to occur when (1) the level of technology readiness is low, (2) the technology is in the early stages of its lifecycle, (3) the R&D budget is low, or (4) the R&D research period is long.

Discussion and conclusions

Discussion and policy implications

With its multi-contextual framework consisting of technological and R&D resource allocation contexts, this study answers the question: what drives technology convergence? Based on the multi-assignation analysis of technology domains, we employed a rich and novel dataset from a nearly complete enumeration survey of the technologies derived from government-supported R&D programs in South Korea from 2001 to 2009. Overall, the above empirical results strongly support our multi-contextual framework, with the exception of the explanations related to the scale of funding. To conclude, it is useful to summarize our findings by discussing their implications in increasing opportunities for creating technology convergence and the extent to which policy actions can foster this process. In this respect, our analysis produced the following findings.

First, technology convergence occurs within a context of potential costs and benefits, as indicated by the influence of the level of technology readiness and the stage of the technology lifecycle on the probability of technology convergence. Accordingly, in terms of efficacious policy, means of promoting technology convergence should aim to reduce costs and increase benefits.

For example, improved institutional networks and new models of financing and of assessment criteria can be effective policy/managerial tools for promoting technology convergence. In particular, convergence-oriented networking programs may help reduce transaction costs by promoting vigorous communication among different techno-scientific domains. Government and quasi-governmental bodies such as funding agencies hold a number of network meetings to give researchers opportunities to network and understand other disciplines; however, one can be skeptical about the efficacy of such network activities given the absence of tangible outputs deriving from them. In response to this skepticism, we suggest that such network activities could be worthwhile because reduction of the cognitive distance could potentially lower the technology convergence cost at the social level.

Another finding of this study is that the scale and duration of financial R&D affect the probability of technology convergence. Contrary to the common understanding that large-scale funding enables researchers to reach more technological domains, our results show that more funding instead aggravates the technology-convergence environment. This negative effect of R&D budget scale on technology convergence sheds light on an adversarial aspect of affluence of R&D resources: time resource positively affects the probability of creating technology convergence while financial resource negatively affects it. One reason could be the great expectations of governing entities and corresponding changes for R&D entities' actions. The amount of funding for a project is generally considered to represent its perceived importance, and the commitment of managers to fund-recipients' individual projects is proportional to that perceived importance (Payne, 1995). Therefore, R&D activities in which governing bodies invest relatively large amounts tend to be of strict missions with strategic purpose, while the others tend to be more spontaneous and more oriented toward encouraging creativity and network activities (Jeong and Choi, 2012).

Since the exchange of essential expertise across techno-scientific domains is essential to successful innovation management, networking and creativity-oriented R&D projects, which would accompany smaller funding, are more likely to facilitate technology convergence. In other words, R&D projects with substantial funding, which would be conducted under their relatively strict missions, can obstruct the possibility of boundary-spanning across technological domains.[11] In fact, the study of science convergence posits a similar idea: researchers in small laboratories tend to be involved in diverse research areas, whereas those in larger laboratories tend to focus on fewer areas (Carayol and Thi, 2005).

Our results suggest what would happen if governing entities shoot for increasing the rate of innovation, i.e., when R&D duration is shortened. They may wish to accelerate the speed of R&D in the name of improving efficiency; they might hope to derive economic benefits from doing so. However, in the long term, shortening the R&D period limits the possibility of securing technology convergence, the potential source of future competitiveness. Likewise, given the same R&D timespan, allocating more financial resources would increase R&D output but hamper the possibility of securing technology convergence. Hence, policymakers and managers involved in nurturing technology convergence should consider a balance between short- and long-term outcomes heir resource management actions.

How should a manager/policymaker approach the paradoxical relationship? One solution to the negative impact of funding is to establish large-scale technology convergence-oriented R&D programs. However, the impact of such R&D programs may be only marginal, since the scope of such programs is eventually limited and because general R&D programs may remain as the majority. The choice of policy for a persistent solution might be to improve innovation systems as well as mitigating obstacles to innovation in technology convergence. The endogenous evolution of a system may increase not only the capacity and efficiency of knowledge production but also the possibility of boundary-spanning innovative activities.

Regarding the differentials of technological domains, the results support the common notion for nano-technology. It is often believed to be "building technology" that results in new ways of manufacturing, as well as new novel functions, when converging with other technologies in different domains (Roco and Bainbridge, 2002). Culture-technology also appears to relate positively to technology convergence, while information-technology and bio-technology turn out to be negatively correlated to technology convergence, which is inconsistent with the common belief on information-technology as an "enabler". However, proving whether the conjectures are valid may require further thorough investigation. The results are reporting not the frequency of technology convergence but the likelihood of being engaged in technology convergence. More importantly, we cannot fully rule out the possibility of sample biases—the likelihood can simply vary by technological trend.

As for organizational heterogeneity, one can simply surmise that government research institutes and universities share many characteristics by virtue of being public institutes, but the results show that they are significantly different vis-à-vis their tendencies to develop converging technologies. However, profound reasoning on this phenomenon may require an in-depth understanding of the difference between organizational contexts.

[11] Admittedly, a large R&D project can consist of various subordinate research goals, which can create room for doubt about whether a large R&D project really addresses narrow technological domains. However, the way in which subordinate research goals are planned is primarily based on the organizational structure of the goals; otherwise, research groups would not be able to justify the large volume of R&D projects in competition for funding.

Limitations and further research

Our study has certain limitations. The novel and unique dataset that enabled this study presents a restricted view by dealing only with technology convergence among R&D projects in heterogeneous technology domains. Presumably, technology convergence can occur within the scope of a single project and can take the form of patents, although technological knowledge can appear in other mediums or evolve through a confluence of existing relevant technologies (Arthur, 2009).[12] Thus, diverse approaches—as in studies on science convergence—should follow and verify our findings. Second, although our dataset covers a decade of fully government-supported R&D projects, it cannot show activities not funded through government support (e.g., independent, private-sector R&D programs). Analysis can be distorted by a firm's motivations for participating in government-supported R&D programs. Furthermore, although our indicator for measuring convergence originating from government-supported R&D projects gives insight into the advent of technology convergence, it does not offer a conclusive picture of the nature of technology convergence occurring in the private sector. Finally, regional characteristics could affect determinants and change the study results. Although South Korea is the fourth-most prolific generator of patent applications worldwide and has strong industries closely involved in intellectual assets (e.g., IT and manufacturing industries), generalizing our findings from regional phenomena to universal phenomena requires evidence from other regions. For example, national differences in regulations obstructing convergence at the industry or technology level could play an important role in nurturing technology convergence. These data-related issues can also cast doubt on the unique finding of this research, the negative relationship between financial resource for R&D and likelihood of creating technology convergence. Although more than 50,000 patents are included in our analysis, theoretical ground for the relation is still neither fully understood by previous literature nor firmly supported by other empirical studies. This aspect suggests that the relationship not be concluded but remain as an open question and be investigated by follow-up studies for generality.

This study suggests certain directions for future research. First, the actual economic benefits of technology convergence can be studied. Science convergence studies have sought to measure the advantages of science collaboration by using citation analysis. Similarly, citation analysis or assessments of patent quality can widen our understanding of technology convergence and R&D entities' strategies. Second, empirical and thorough demonstrations of complementarity among technologies can follow. Finally, as mentioned, a study with more generic data for different regions and approaches to technology convergence should follow to strengthen the generalizability of our results.

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[12] Similar limitations can be debated regarding this and previous science-convergence research that uses co-authorship analysis and multi-assignation analysis (Morillo et al., 2003).

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