Impact of Cooperative R&D Projects on ICT-Based Technology Convergence

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This study examines how the characteristics of cooperative research and development (R&D) projects in the public domain impact information and communication technology (ICT) convergence. Based on the analysis of 416 cooperative R&D projects under the ICT-based industry convergence R&D program in Korea, the study finds that the characteristics of cooperative R&D projects significantly impact ICT convergence. Moreover, the participation of public research institutes and universities is critical for ICT convergence compared with that of firms. However, in firm-to-firm cooperation, the participation of small and medium enterprises contributes to cross-sectional convergence, while the participation of large firms leads to overall and longitudinal convergence. R&D inputs such as the number of partners and government subsidies exhibit an inverted U-shaped relationship (negative quadratic effect) with technology convergence. Project duration and homogeneous partners are also critical factors for ICT convergence. The results indicate several implications and guidelines on how to effectively organize cooperative R&D projects to facilitate technology convergence.

Keywords: Technology convergence, Cooperative R&D projects, R&D input, Project duration, Homogeneity of partners.

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I. Introduction

The Korean government developed a five-year national master plan for technology convergence in 2008. Based on this plan, the government reorganized a variety of existing research and development (R&D) projects, and preferentially supported such projects in the technology convergence domain. The National Science and Technology Commission of Korea defines technology convergence as technologies that lead to economic, societal, and cultural changes by introducing creative values that come from synergic combinations of these technologies [1]. The definition, from the industrial R&D perspective, is closely related to the fact that the government would make significant efforts to combine science, technology, and industries to create new markets and industries. Among the major programs in this plan, an information and communication technology (ICT) based industry convergence R&D program deals with industrial technologies in the areas of semiconductors, displays, light-emitting diodes (LEDs), home networks, robotics, plant engineering, medical devices, and manufacturing, and involves a wide range of stakeholders from both industry and academia.

The participants of the ICT-based industry convergence R&D program make efforts to acquire complementary assets beyond their boundaries to cope with increasing complexity, the multidisciplinary nature of R&D research, and shortened technology life-cycles [2]. They also expect better outcomes through collaboration with other participants [3]. Although prior studies have argued that R&D cooperation is an effective way to acquire complementary assets, limited information exists on how the cooperative R&D projects are related to technology convergence.

This study examines how the characteristics of cooperative R&D projects in the public domain impact ICT convergence. ICT convergence is a subset of technology convergence. ICT is a core domain that facilitates various types of technology convergence, and can thus be a catalyst for developing converging technologies. The Korean government has supported ICT-based R&D projects to develop converging technologies through the national master plan, and hence, several datasets are available for analyzing the association between R&D cooperation and ICT convergence. As such, this study focuses on ICT convergence instead of technology convergence in general.

In addition, this study employs three levels of ICT convergence, namely monotonous, homogeneous, and heterogeneous convergence, to analyze the effects of cooperative R&D projects' characteristics on ICT convergence. The three levels indicate the degree of convergence, which explains the extent to which different technologies are combined to develop a new converging technology. Therefore, the impact of R&D projects' characteristics on the three levels of convergence may vary, and this could have significant implications for industry and academia.

The remainder of the paper is organized as follows. Section II provides an overview of previous theoretical and empirical literature. Section III develops the hypotheses explaining ICT convergence regarding cooperation characteristics. Section IV describes the datasets, variables, statistical methodology, and results of statistical analyses. Finally, the implications from the perspective of innovation strategy and R&D cooperation, and the study's limitations are discussed in Section V.

II. Literature Review

1. Technology Convergence

Technology convergence is a process that blurs the borders between previously distinct technologies [4], so that it satisfies existing and changing needs in an innovative way by enhancing the efficiency of existing products or by suggesting new functionalities [5]. Such an erosion of boundaries is a sequential process from science and technology to industry [4].

Once technology convergence is widespread, it can be an enabler for radical innovations as well as for industrial evolution. Technology convergence stimulates business model innovations, makes entirely different industries compete, and eventually leads to industry convergence [6]–[8]. Innovative business models triggered by technology convergence make incumbents such as big telephony or pharmaceutical firms vulnerable to new market entrants [7]–[9]. The transformative power of technology convergence can offer exceptional value to the market as a competitive advantage of new entrants.

When technology convergence becomes industry convergence, certain industry-specific drivers become more influential and tend to accelerate this disruptive process. In the ICT sector, common protocols and standards are those catalysts turning technology convergence into industry convergence, because standards and protocols comprehensively deal with various service qualities and features [10].

Due to the transformative power of technology convergence, prior literature considers it disruptive innovation or a special case of incremental innovation becoming disruptive [9]. However, ICT convergence has been regarded as important innovative performance, and can lead to developing new products, services, or innovative business models. Additionally, ICT convergence can create new market segments and reorganize existing markets. Additional innovations, either disruptive or incremental, can be initiated from ICT convergence [6]–[8]. Therefore, ICT convergence can be as an enabler or basis for various R&D activities. This paper considers ICT convergence as a major R&D performance, and examines the association between R&D cooperation and ICT convergence.

2. R&D Cooperation

From the resource-based perspective, R&D cooperation is beneficial in innovation performance [11]–[15] despite risks such as increased transaction costs, delays, and cooperation failure [3], [16]. The necessity for R&D cooperation has been reinforced by the ever-increasing dynamics of technologies. Organizations have tried to take full advantage of R&D cooperation by looking for similar or complementary resources of R&D inputs (for example, funds and human resources) and by trying to achieve economies of scale and scope of R&D outputs (for example, innovation and markets). However, high transaction costs for coordinating different parties and the difficulties of managing different incentives frequently cause undesirable results and even project failure [13], [15], [16]. Consequently, the relationship between the characteristics of cooperative R&D projects and their performance has been an important research topic in innovation studies.

Firms cooperate with those having complementary or similar resources to reduce risks and costs [11], [12]. Firms also rely on public institutes and universities, since their public research partners are major scientific and technological knowledge suppliers. Selecting the right partners in R&D cooperation is critical for innovation performance [14], [15]. Prior studies on R&D cooperation noted that the effect of R&D cooperation varies depending on the partner type and targeted innovation [11], [13], [15], [17], [18]. Table 1 presents partner types and their benefits in R&D cooperation.

R&D cooperation is not always beneficial, especially when

Table 1. Partners and benefits in R&D cooperation.

Partners	Benefit for innovation
Large firms	Patenting, realization of new products
New and small firms	Radical innovations
Public institutes	Patenting
Universities	New product sales

managing partnerships is difficult. R&D projects may be withdrawn due to difficulties in managing partnerships and may face cooperation failure [16]. The characteristics of R&D projects can indicate "how the project is organized," and it might be critically influential on R&D performance. Prior studies on R&D cooperation show that the characteristics of R&D projects, such as the number and type (homogeneous /heterogeneous) of partners, budget size, and duration of projects, critically impact project R&D performance. However, how the characteristics of R&D cooperation influence technology convergence is unknown.

III. Hypotheses Development

1. Types of R&D Partners

This study focuses on cooperative R&D projects funded by the Korean government. The participants in these R&D projects are from industry or public research institutions, including universities. According to the resource-based view, each participating organization has different capabilities and capacities in terms of R&D, production, and marketing [11]–[15]. Large firms, small and medium-sized enterprises (SMEs), and public research institutions (universities) have their own strengths in specific domains. Therefore, this study divides R&D partners into three groups, and examines the effects of R&D partner types on ICT convergence.

Participating in cooperative R&D projects is beneficial for enhancing R&D performance, such as productivity and patenting [11], [13], and the effective combinations of partners determine the levels of performance [19]. Additionally, the success of cooperative R&D projects depends on the structure and content of cooperation [14]. Larger firms are less likely to face cooperation failures, since they have greater internal R&D capacities [14], [16]. Larger firms also have better absorption capabilities due to the existence of an R&D department and a higher share of R&D personnel [2], [11]. In terms of patenting, larger firms tend to be more familiar with the procedure and management of patenting than SMEs, and have higher aspiration for innovation, especially within their business areas [2]. Cooperative R&D with large firms might be easier to achieve technological success from the beginning [14]. It could also better facilitate commercialization from R&D and can greatly contribute to the success of projects [15], [20], [21] and R&D performance [11], [13]–[16]. Therefore, ICT convergence (one type of R&D performance) may be positively affected by cooperative R&D with large firms.

Hypothesis 1a*: Participation of large firms in R&D cooperation positively influences ICT convergence.*

Although large firms have greater internal R&D capacities and cope better with high R&D costs, they can be less sensitive to innovation due to their larger market shares. Conversely, SMEs having organizational flexibility and agility in making decisions can be more successful in process innovation [22], thereby their involvement in cooperative R&D projects being more beneficial. Furthermore, a large in-house R&D capacity becomes less important, while the significance of inter-organization R&D cooperation is increasing for innovation [18]. The competence changes and quick responses for radical innovation, such as technology convergence, may be difficult for large firms, so radical innovations are associated rather with SMEs [17]. Therefore, this study posits that:

Hypothesis 1b*: Participation of small and medium firms in R&D cooperation positively influences ICT convergence.*

From the resource-based view, universities and public re-search institutes are important sources of scientific and technological knowledge in the innovation process. Cooperation with public research institutes and universities is beneficial for firms that have limited resources and experience [11], and they are preferentially chosen by firms in sectors that exhibit faster technological advancement [13]. The involvement of universities and public research institutes in R&D cooperation positively affects R&D performance, such as patenting [12], [14], [15] and productivity in innovative sales [13], despite potential cooperation failure [16]. Thus, cooperative R&D with universities or public research institutes may positively affect R&D performance, so this study posits that:

Hypothesis 1c*: Participation of universities or public research institutes in R&D cooperation positively influences ICT convergence.*

2. Characteristics of R&D Projects

Cooperative R&D projects are an efficient way to access required resources by pooling the complementary or similar resources of multiple partners. Therefore, the size of cooperative R&D projects is an important factor for technological success [23]. When the number of partners is smaller, the motivation for R&D cooperation may decrease due to the burden of the project for each partner and the difficulties in obtaining resources [19]. Consequently, the likelihood of realizing product innovations increases with the number of partners in cooperative R&D [3]. Conversely, when the number of partners is larger, the higher costs of coordination and administration may negatively impact team cooperation, communication, and R&D output due to the potential free-riding behaviors [15]. Therefore, the number of partners has a diminishing marginal effect on innovative performance, so it is hypothesized that:

Hypothesis 2*: The number of partners in R&D cooperation exhibits an inverted U-shaped relationship with ICT convergence.*

Some researchers argue that the innovation output of cooperative R&D projects is eventually produced by the subsidies granted to participants and the R&D budgets pooled [21]. Project budget has a significant impact on R&D performance [15] by reducing the duration to commercialization [23]. With public subsidies, participants of cooperative R&D projects obtain additional financial resources that may increase the probability of project success [14]. Sakakibara and Branstetter [21] even suggest that their empirical results, in which a larger budget for a R&D cooperation results in fewer patents, are driven by the truncation of patent data. On the other hand, large subsidies may have negative effects, since a large amount of money enables trying risky projects with a low possibility of success, which would otherwise not be attempted. In addition, projects with government subsidies or larger budgets can have no critical impact on technical success [14], [23]. Therefore, the project budget can have a diminishing marginal effect on R&D output [28], and this study posits that:

Hypothesis 3*: The project budget of cooperative R&D projects exhibits an inverted U-shaped relationship with ICT convergence.*

Schwartz and others [15] argue that project duration has a positive impact on the innovation output of R&D projects. However, they found that project duration is insignificant or negatively influences the number of patents, especially in firm-to-firm cooperation. Nevertheless, if the project duration is short, reciprocal exchanges of knowledge among partners may be not enough, and this can lower the probability of success, while possibly triggering opportunistic behavior and free-riding higher at the same time. The probability of technical success of a project increases with project duration [23], so time is a critical factor for understanding and implementing the knowledge provided by cooperating partners, especially when they are from different industry sectors. This holds particularly true for exchange of tacit knowledge, which is an interacting process based on trust and reciprocity among partners [15]. Therefore, it is hypothesized that:

Hypothesis 4*: The project duration of cooperative R&D projects positively influences ICT convergence.*

3. Homogeneity of R&D Partnerships

One of the main concerns of organizing cooperative R&D projects is finding adequate partners to achieve the results sought by the cooperation, since pooling adequate complementary resources can be performed by appropriate partners [24]. In this resource-based perspective, recent studies explore the effects of different types of partners, and find that characteristics of cooperative R&D, such as diversity of members, are more important than R&D input in explaining technological performance [11], [14]. Projects established mainly by universities and/or research institutes may produce less applied results, while a greater diversity of partners can cause a lack of shared vision and communication. Regarding exploration projects, in which participants tend to create technological knowledge through exploring new opportunities such as ICT convergence, homogeneous partners have a positive impact on innovative performance [19]. Therefore, it is posited that:

Hypothesis 5a*: The homogeneity of partnership in R&D cooperation positively influences ICT convergence.*

In the meantime, exploitation projects are rather associated with the use of existing knowledge and technology to improve efficiency and returns [12]. In exploitation projects, it is necessary for both creators and users of knowledge to participate. Universities, public research institutes, and firms are common partners in these types of projects. If projects are only formed by firms, homogeneous partners may negatively influence R&D output. Thus, this study posits that:

Hypothesis 5b*: The homogeneity of partnership negatively influences ICT convergence in firm-to-firm cooperation.*

IV. Research Methods

1. Data and Variables

We have randomly selected 416 cooperative R&D projects from the ICT-based industry convergence R&D Program in Korea. The R&D projects under this program aim to develop ICT-based converging technologies, including displays, LEDs, home networks, robotics, medical devices, and others. The data about the R&D projects from the ICT-based industry convergence R&D Program were stored in the National Science and Technology Information Service database. We researched and collected the patents from the selected projects using the Korea Intellectual Property Strategy Institute database. We found 5,760 patents that have more than two different International Patent Classifications (IPCs), and replaced every IPC of a patent with the corresponding technology field and area based on the IPC-Technology Concordance Table from the World Intellectual Property Organization [24]. The first and second IPCs of each patent are adopted for matching with technology classification. Schmoch [24] includes the additional IPCs of recent technologies, such as wireless communications, that are not specified in the original classification. Additionally, Kim [25] suggests that a patent is non-converging when it has only one subclass-level IPCs that belongs to the ICT industry, a patent is homogeneous when it has plural subclass-level IPCs in the ICT industry, and heterogeneous when it has plural subclass-level IPCs that belong to different industries other than the ICT industry.

We define three different types of technology convergence: monotonous, homogeneous, and heterogeneous based upon Kim's classification [25]. Monotonous convergence indicates that a patent has two IPCs in the same technology field. Homogeneous convergence refers to a patent that has IPCs in two different technology fields, but in the same technology area. Heterogeneous convergence is defined as a patent that has IPCs in two different technology areas. The three types of technology convergence indicate the degree of convergence. Heterogeneous convergence is the highest level of convergence, which explains that more dissimilar component technologies are combined to develop a high-level converging technology. Monotonous convergence refers to the lowest level of technology convergence, which is achieved by the combination of more similar component technologies. Depending upon the levels of technology convergence, the characteristics of cooperative R&D projects are expected to influence technology convergence differently. Typically, more R&D resources (for example, budget, time, and human resources) are needed to achieve the higher level of technology convergence than the lower one. Therefore, we examine the effect of R&D project characteristics on the different levels of technology convergence.

Table 2 presents the dependent and independent variables of this study and Appendix A presents the descriptive statistics of the variables. We added the squared R&D inputs (number of partners, budget) to test a negative quadratic effect (inverted U-shaped relationship) of R&D inputs on ICT convergence. The homogeneity of partners is measured by the Gini coefficient, which is commonly used as a measure of inequality in previous literature. The Gini coefficient represents the diversity of participants (0: minimal homogeneity, 1: maximal homogeneity) [19]. Government subsidy (Govfund, Govfund_sq) and private. funding (Prvfund, Prvfund_sq) variables were log-transformed to prevent low coefficients.

Table 2. Dependent and independent variables.

Variables		Description
Dependent variables	Mono	Number of monotonous convergences
	Homo	Number of homogeneous convergences
	Hetero	Number of heterogeneous convergences
	Total	Total number of convergences
Independent variables	SME dummy	Participation of small and medium firms (0 or 1)
	BE dummy	Participation of large firms (0 or 1)
	Public dummy	Participation of public partners (0 or 1)
	Partners	Number of partners
	Partners_sq	Squared number of partners
	Govfund	Amount of government subsidy
	Govfund_sq	Squared amount of government subsidy
	Prvfund	Amount of private funding
	Prvfund_sq	Squared amount of private funding
	Period	Duration of the R&D project
	Homogeneity	Homogeneity of partners (0 –1)

Table 3. Over-dispersion of dependent variables.

Over-dispersion	Dependent variables			
	Total	Hetero	Homo	Mono
Variance to mean ratio (VMR)	26.7	13.8	11.6	11.2
Coefficient of variation	1.4	2.0	1.4	1.62

2. Estimation Model

Table 3 shows that the four dependent variables in this study have an over-dispersion problem. These dependent variables are non-negative and integer count variables. The existence of heteroscedasticity and abnormal residuals can be concerns, since modeling errors are not uniform and variances do vary with modeling effects. To overcome this problem, we need a non-linear regression model, such as Poisson or negative binomial regression models.

Poisson models assume the conditional mean and variance of the distribution are equal (VMR = 1). Here, negative binomial regression models may be better to deal with over-dispersion data (VMR > 1) [26]. Therefore, this study employed the negative binomial model for analysis. Appendix B presents the details of the negative binomial regression models.

V. Results

We tested three models to control possible differences in the effects of independent variables due to multicollinearity. Model 1 tested the impact of the participation of different partners, homogeneity, and period. Model 2 included additionally the impact of R&D inputs, and model 3 tested the impact of squared forms of R&D inputs. All three models show a significant relationship between the dependent and independent variables. Pearson correlation values in Table 4 are below the 0.70 threshold. We additionally estimated variance inflation factors (VIF) values, from 1.158 to 1.957, as shown in Table 5, which means no multicollinearity problems exist (VIF < 5). As such, the models are robust and suggest good fitness.

In addition to models 1, 2, and 3 with the full sample, we examined models 4, 5, and 6 with the inter-firm sample. To test for multicollinearity between R&D inputs and their squared forms (Partners_sq, Govfund_sq, Prvfund_sq), we performed log likelihood ratio tests between models 2 and 3, and between models 5 and 6. Models 2 and 3 have no multicollinearity, since likelihood ratios (LR) are 11.896, 17.944, 18.942, and 19.184, respectively. The LR values are larger than 7.815, which is the critical value of LR when the p-value is 0.05 and degrees of freedom 3. For models 5 and 6, LRs are from 2.582 to 5.838, thus excluding model 6.

Table 6 presents the results from negative binomial regression analysis. For the *mono convergence*, participation of large firms has a negative effect (model 3), but they are significantly positive in inter-firm cooperation (model 4). Participation of small and medium firms has also a negative effect (models 2 and 3), but they are not significant in inter-firm cooperation. In addition, public partners such as universities or public institutes have a positive effect (model 1). Homogeneity

Table 4. Pearson correlation matrix.

Variables	1	2	3	4	5	6	7	8
1. SME dummy	1	N/A	N/A	N/A	N/A	N/A	N/A	N/A
2. BE dummy	0.125*	1	N/A	N/A	N/A	N/A	N/A	N/A
3. Public dummy	–0.087	0.042	1	N/A	N/A	N/A	N/A	N/A
4. Period	–0.275	0.018	0.194	1	N/A	N/A	N/A	N/A
5. Homogeneity	–0.266	–0.029	–0.447	–0.132	1	N/A	N/A	N/A
6. Govfund	0.011	0.083	0.154	0.074	–0.010	1	N/A	N/A
7. Prvfund	0.206	0.443	0.033	–0.044	–0.043	0.548	1	N/A
8. Partners	0.254	0.383	0.265	0.000	–0.335	0.216	0.327	1

* Indicates significant correlations at the 5% level.

Table 5. Variance inflation factors values.

Variables	VIF values	Variables	VIF values
1. SME dummy	1.348	5. Homogeneity	1.603
2. BE dummy	1.458	6. Govfund	1.957
3. Public dummy	1.416	7. Prvfund	1.537
4. Period	1.158	8. Partners	1.471

of partners and project duration are not significant for this level of convergence. R&D inputs tend to have a positive impact (models 3 and 5), except for private funding, but too much R&D inputs have a clearly negative effect on mono convergence. Therefore, they exhibit an inverted U-shaped relationship with mono convergence (model 3). Considering only upward-side effects of R&D inputs on inter-firm cooperation, the number of partners and government subsidies have positive effects, whereas private funding is negatively influential. However, this is not of main concern of this study.

For the *homo convergence*, participation of large firms is not significant in the full sample, while it has a positive effect in inter-firm cooperation (model 4), such as at the mono convergence. Participation of small and medium firms has a negative effect in the full sample (model 1, 2 and 3) as well as in inter-firm cooperation (model 5). However, the participation of public partners (models 1, 2, and 3) is strongly positive, contrary to that of SMEs. The homogeneity of partners comes to be positively influential (models 1 and 3), while project duration is still insignificant. R&D inputs, such as the number of partners and project budget (government subsidies), have an inverted U-shaped relationship with the homo convergence, except that private funding is not significant (model 3).

For the *hetero convergence*, participation of large firms is not significant in all the models, however, participation of small and medium firms is positive (model 4) in inter-firm cooperation. Participation of public partners is also positive (model 1). Homogeneity of partners has a positive effect (model 1). Additionally, project duration is strongly positive and significant (models 1, 2, and 3) for hetero convergence. Longer project duration increases the possibility of technical success [23]. However, it comes to be less critical for longitudinal (mono and homo) convergence, while it is more critical for cross-sectional (hetero) convergence. Moreover, government subsidies show an inverted U-shaped relationship with hetero convergence. However, the number of partners and private funding has no such relationship.

For *overall ICT convergence*, the participation of large firms in inter-firm cooperation has a positive effect (model 4), while it is not significant in the full sample (models 1, 2, and 3). The participation of small and medium firms is negative (models 2 and 3), whereas that of public partners is strongly positive for ICT convergence (models 1, 2, and 3). The homogeneity of partners (models 1 and 3) and project duration (model 1) have a positive effect. R&D inputs exhibit an inverted U-shaped relationship with ICT convergence. In terms of private funding, the relationship is confirmed only on the downward side. Finally, the homogeneity of partners in firm-to-firm cooperation is not significant for all convergence, although the coefficients imply a negative impact on convergence as

Table 6. Results of negative binomial regression analyses.

Dependent var. **mono** / Independent var.	Full sample						Inter-firm sample			
	Model 1		Model 2		Model 3		Model 4		Model 5	
	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.
BE dummy = 1	0.034	0.840	–0.176	0.275	**–0.335***	**0.026**	**1.399***	**0.002**	0.586	0.153
SME dummy = 1	–0.289	0.141	**–0.553***	**0.004**	**–0.666***	**0.001**	0.513	0.524	–0.949	0.210
Public dummy = 1	**0.704***	**0.030**	0.225	0.443	0.195	0.466	N/A	N/A	N/A	N/A
Partners	N/A	N/A	0.030	0.243	**0.153***	**0.007**	N/A	N/A	**0.244***	**0.001**
Partners_sq	N/A	N/A	N/A	N/A	**–0.007***	**0.008**	N/A	N/A	N/A	N/A
Govfund	N/A	N/A	**0.160***	**0.000**	**0.230***	**0.000**	N/A	N/A	**0.596***	**0.000**
Govfund_sq	N/A	N/A	N/A	N/A	**–0.004***	**0.035**	N/A	N/A	N/A	N/A
Prvfund	N/A	N/A	0.003	0.953	0.196	0.113	N/A	N/A	**–0.680***	**0.007**
Prvfund_sq	N/A	N/A	N/A	N/A	**–0.029****	**0.067**	N/A	N/A	N/A	N/A
Period	0.005	0.427	–0.003	0.581	0.002	0.632	–0.014	0.468	–0.012	0.452
Homogeneity	1.520	0.271	0.213	0.879	1.563	0.253	N/A	N/A	N/A	N/A
	N/A	N/A	N/A	N/A	N/A	N/A	–4.827	0.524	–6.371	0.301

Dependent var. **homo** / Independent var.	Full sample						Inter-firm sample			
	Model 1		Model 2		Model 3		Model 4		Model 5	
	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.
BE dummy = 1	0.032	0.802	–0.072	0.554	–0.195	0.104	**0.933***	**0.037**	0.097	0.745
SME dummy = 1	**–0.284****	**0.087**	**–0.467***	**0.001**	**–0.546***	**0.000**	0.104	0.870	**–0.860****	**0.067**
Public dummy = 1	**1.026***	**0.000**	**0.624***	**0.002**	**0.501***	**0.010**	N/A	N/A	N/A	N/A
Partners	N/A	N/A	0.036	0.104	**0.164***	**0.000**	N/A	N/A	**0.145***	**0.027**
Partners_sq	N/A	N/A	N/A	N/A	**–0.007***	**0.000**	N/A	N/A	N/A	N/A
Govfund	N/A	N/A	**0.165***	**0.000**	**0.263***	**0.000**	N/A	N/A	**0.530***	**0.001**
Govfund_sq	N/A	N/A	N/A	N/A	**–0.006***	**0.000**	N/A	N/A	N/A	N/A
Prvfund	N/A	N/A	–0.040	0.312	0.046	0.618	N/A	N/A	**–0.394***	**0.045**
Prvfund_sq	N/A	N/A	N/A	N/A	–0.014	0.240	N/A	N/A	N/A	N/A
Period	0.004	0.419	–0.003	0.512	–0.001	0.725	–0.013	0.361	–0.003	0.772
Homogeneity	**2.585***	**0.035**	1.011	0.345	**2.046***	**0.042**	N/A	N/A	N/A	N/A
	N/A	N/A	N/A	N/A	N/A	N/A	–2.661	0.679	–6.922	0.210

Dependent var. **hetero** / Independent var.	Full sample						Inter-firm sample			
	Model 1		Model 2		Model 3		Model 4		Model 5	
	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.
BE dummy = 1	0.134	0.374	0.105	0.592	0.044	0.831	0.555	0.177	0.309	0.528
SME dummy = 1	–0.186	0.430	–0.190	0.272	–0.204	0.214	**1.245***	**0.038**	0.366	0.494
Public dummy = 1	**0.600***	**0.042**	0.127	0.628	0.073	0.773	N/A	N/A	N/A	N/A
Partners	N/A	N/A	0.024	0.289	0.048	0.260	N/A	N/A	0.033	0.719
Partners_sq	N/A	N/A	N/A	N/A	–0.001	0.345	N/A	N/A	N/A	N/A
Govfund	N/A	N/A	**0.154***	**0.000**	**0.275***	**0.000**	N/A	N/A	**0.623***	**0.000**
Govfund_sq	N/A	N/A	N/A	N/A	**–0.007***	**0.003**	N/A	N/A	N/A	N/A
Prvfund	N/A	N/A	–0.025	0.641	0.030	0.820	N/A	N/A	**–0.617***	**0.001**
Prvfund_sq	N/A	N/A	N/A	N/A	–0.010	0.452	N/A	N/A	N/A	N/A
Period	**0.023***	**0.001**	**0.017***	**0.001**	**0.018***	**0.000**	0.020	0.242	0.023	0.150
Homogeneity	**3.113****	**0.079**	1.043	0.517	1.533	0.332	N/A	N/A	N/A	N/A
	N/A	N/A	N/A	N/A	N/A	N/A	–0.255	0.977	–6.116	0.429

Dependent var. total / Independent var.	Full sample						Inter-firm sample			
	Model 1		Model 2		Model 3		Model 4		Model 5	
	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.
BE dummy = 1	0.073	0.538	–0.059	0.609	–0.175	0.126	**0.964***	**0.008**	0.245	0.441
SME dummy = 1	–0.250	0.140	**–0.409***	**0.001**	**–0.472***	**0.000**	0.760	0.230	–0.360	0.455
Public dummy = 1	**0.794***	**0.001**	**0.373****	**0.053**	**0.327****	**0.063**	N/A	N/A	N/A	N/A
Partners	N/A	N/A	0.033	0.106	**0.111***	**0.000**	N/A	N/A	**0.150***	**0.006**
Partners_sq	N/A	N/A	N/A	N/A	**–0.004***	**0.000**	N/A	N/A	N/A	N/A
Govfund	N/A	N/A	**0.160***	**0.000**	**0.256***	**0.000**	N/A	N/A	**0.570***	**0.000**
Govfund_sq	N/A	N/A	N/A	N/A	**–0.006***	**0.000**	N/A	N/A	N/A	N/A
Prvfund	N/A	N/A	–0.017	0.657	0.105	0.218	N/A	N/A	**–0.499***	**0.001**
Prvfund_sq	N/A	N/A	N/A	N/A	**–0.019****	**0.080**	N/A	N/A	N/A	N/A
Period	**0.010****	**0.057**	0.003	0.346	0.004	0.215	0.001	0.949	0.005	0.618
Homogeneity	**2.384***	**0.041**	0.789	0.429	**1.819****	**0.051**	N/A	N/A	N/A	N/A
	N/A	N/A	N/A	N/A	N/A	N/A	–2.416	0.702	–6.021	0.262

Table 7. Summary of the results.

Hypothesis (independent var.) \ Dependent var.	Mono		Homo		Hetero		Summary
	Full model	Inter-firm model	Full model	Inter-firm model	Full model	Inter-firm model	
H1a (Large Firms)	N/A	Supported	N/A	Supported	N/A	N/A	Participation of large firms positively influences mono and homo convergence in inter-firm cooperation.
H1b (Small and Medium Firms)	N/A	N/A	N/A	N/A	N/A	Supported	Participation of small and medium firms positively influences hetero convergence in inter-firm cooperation.
H1c (Public Partners)	Supported	N/A	Supported	N/A	Supported	N/A	Participation of public partners positively influences mono, homo, and hetero convergence in the full model.
H2 (Number of Partners)	Supported	N/A	Supported	N/A	N/A	N/A	Number of partners exhibits an inverted U-shaped relationship with mono and homo convergence in the full model.
H3 (Project Budget)	Supported	N/A	Supported	N/A	Supported	N/A	Project budget exhibits an inverted U-shaped relationship with mono, homo, and hetero convergence in the full model.
H4 (Project Duration)	N/A	N/A	N/A	N/A	Supported	N/A	Project duration positively influences hetero convergence in the inter-firm cooperation.
H5a (Homogeneity of Partners)	N/A	N/A	Supported	N/A	Supported	N/A	Homogeneity of partnership positively influences homo and hetero convergence in the full model. However, H5b is not supported.

assumed.

Table 7 presents the summary of the analysis results. Firms tend to be knowledge recipients in cooperative R&D projects. However, in the absence of major knowledge suppliers, such as in inter-firm cooperation, they tend to be knowledge providers, and their characteristics are discriminatively influential. Participation of larger firms is beneficial for more longitudinal convergence, presumably due to their existing capabilities and access to markets, and that of SMEs is positive for cross-sectional convergence perhaps due to their agility and adaptability. Advantages of larger firms for innovation, such as greater internal R&D capacities [14], better absorption capabilities [2], and more knowledge in managing technologies, seem to significantly influence the overall and longitudinal convergence in firm-to-firm cooperation, while the characteristics of SMEs, such as organizational flexibility and quick decision-making processes, are rather associated with radical innovation [17]. Therefore, SMEs have positive influence on hetero convergence in firm-to-firm cooperation. Universities and public research institutes are important sources of innovation, so their involvement seems to be critical for ICT convergence. Homogeneous partners are beneficial for exploratory innovation [19], while they negatively influence exploitative innovation [12]. The results show that the homogeneity of partners is critical, except for mono convergence in the full sample, which might imply homo and hetero convergence tend to have clearer characteristics of explorative innovation. We expect firm-to-firm cooperation to target more exploitative innovation, hence homogeneous partners negatively impacting innovative performance. However, the homogeneity of partners in firm-to-firm cooperation is not significant, although all the coefficients are negative (which might imply inter-firm cooperation is more oriented towards exploitative innovation).

In shorter projects, reciprocal exchanges of knowledge among partners may be difficult, which can be intensified when the knowledge is cross-sectional [15]. From this perspective, project duration can be a more critical factor for more or cross-sectional ICT convergence than for the longitudinal one.

R&D inputs exhibit an inverted U-shaped relationship with ICT convergence. The upward side of the inverted U-shape is clearer than the downward side, which may imply the advantages of having a large number of partners [3] and government subsidies being greater as disadvantages [15]. The number of partners is not significant for the hetero convergence, which may imply that cross-sectional convergence is associated more with “who participates in” than with “how many participate in,” regardless of the advantages and disadvantages of many partners. Compared with government subsidies, which show an inverted U-shaped relationship with ICT convergence, private funding, squared or not squared, tends to be negative. This might be because the amount is trivial, including many zero figures, since non-profit organizations usually do not pool monetary resources for cooperative R&D projects.

VI. Discussion and Conclusion

The results suggest that the participants of cooperative R&D projects can be important predictors of ICT convergence. Firms, large or small, tend to be technology recipients, but they could make up for the lack of major knowledge suppliers. Large firms contribute to longitudinal convergence, which is related with their existing market shares and capabilities, while SMEs lead to cross-sectional convergence due to their agility and adaptability. Additionally, the involvement of universities and public research institutes is critical for ICT convergence. Considering innovative performance (for example, ICT convergence), the government may have no need to intentionally favor SMEs, especially with respect to government subsidies.

The word "convergence" is widespread as, for encouraging technology convergence, the government comprehensively defines convergence. However, we might need more specific guidelines and definitions for better use of budgets and resources.

The duration of government-supported R&D projects has recently shortened to around three years. Time is a critical factor, especially in understanding multidisciplinary knowledge and, when it comes to converging technologies, project duration needs to be carefully taken into consideration.

In terms of ICT convergence, large R&D inputs are not necessarily beneficial, although they could be an efficient way of using resources for participants to help them find adequate knowledge and technology providers.

Although ICT convergence is an important innovative performance, few studies analyze ICT convergence from the perspective of cooperative R&D projects.

As such, our results have implications for the strategic planning of government-funded R&D projects. Nevertheless, they are subject to some limitations that require further research. For instance, we could not collect all the information of R&D projects in the analyzed period under the ICT-based industry convergence R&D program due to the limited data access and difficulties in matching data scattered in different agencies.

Although, we could have suggested optimal points of R&D inputs since inverted U-shaped relationships between R&D inputs and ICT convergence are substantial, this is beyond of the purpose of this paper.

Finally, we only tested the classification scheme among various measuring methodologies of technology convergence based on patents granted in Korea. It might be more meaningful to attempt using other methodologies, such as keyword based or cross citations, to track ICT convergence. In addition, a comparative analysis among different countries is another future research direction in the technology convergence domain.

Appendix A. Descriptive Statistics for Variables

Variables	Min.	Max.	Mean	Std. dev.
Mono	0	62	4.28	6.927
Homo	0	77	5.98	8.316
Hetero	0	77	3.59	7.045
Total	1	211	13.85	19.239
SME dummy	0	1	0.41	0.492
Be dummy	0	1	0.76	0.425
Public dummy	0	1	0.89	0.314
Partners	1	33	5.17	3.407
Partners_sq	1	1,089	38.293	71.336
Govfund*	1.300	224	38.387	36.078
Govfund_sq*	1.690	50,176	2,772.029	6,235.364
Prvfund*	0	93.140	15.041	16.497
Prvfund_sq*	0	8,675.059	497.730	1,115.141
Period	12	106	45.29	14.482
Homogeneity	0.680	0.900	0.821	0.056

* Unit: KRW 100 Million

Appendix B. Negative Binomial Regression Model

When Y is a non-negative integer, the Poisson regression is

$$\text{Prob}\{Y = y_i | x_i\} = \frac{\exp(-\lambda_i)\lambda_i^{y_i}}{\Gamma(1+y_i)},$$

$$\lambda_i = \exp(\alpha + x_i'\beta), y_i = 0,1, \ldots, i = 1, \ldots, N,$$

where x_i is a vector of covariates, i indexes N observations in a random sample, and λ_i represents conditional mean and variance. Log-linear conditional mean and equi-dispersion of the Poisson model is

$$E(y_i | x_i) = Var(y_i | x_i) = \lambda_i.$$

If the non-negative count variable Y is over-dispersed,

$$E(y_i | x_i, \varepsilon_i) = \exp(\alpha + x_i'\beta + \varepsilon_i) = h_i \lambda_i,$$

where $h_i = \exp(\varepsilon_i)$ has a one-parameter gamma distribution, $G(\theta, \theta)$ with mean 1 and variance $1/\theta = k$:

$$f(h_i) = \frac{\theta^\theta \exp(-\theta h_i) h_i^{\theta-1}}{\Gamma(\theta)}, h_i \geq 0, \theta > 0.$$

After integrating h_i out of the joint distribution, we obtain the marginal negative binomial distribution for Y:

$$\text{Prob}\{Y = y_i | x_i\} = \frac{\Gamma(\theta + y_i) r_i^\theta (1-r_i)^{y_i}}{\Gamma(1+y_i)\Gamma(\theta)},$$

$$y_i = 0,1,\ldots,\theta > 0, r_i = \frac{\theta}{\theta + \lambda_i}.$$

By inducing over-dispersion and preserving the conditional mean $(k > 0, \lambda_i > 0)$, the negative binomial regression model provides a better fit than ordinary least squares regression, which assumes that the dependent variable is a continuous value:

$$E(y_i|x_i) = \lambda_i, Var(y_i|x_i) = \lambda_i\left(1+\left(\frac{1}{\theta}\right)\lambda_i\right) = \lambda_i(1+k\lambda_i),$$

where $k = Var(h_i)$. A log-linked negative binomial regression, $\ln y_i = \beta' x_i + \varepsilon_i$, is estimated as a generalized linear model, in which the dependent variable y_i is the number of convergence of the *i*-th cooperative R&D project and x_i a vector of independent variables of the *i*-th project.

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