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An Investigation on the Efficiency of Research Collaborations: Data Envelopment Analysis and Stochastic Frontier Analysis on Bio-technology R&D Projects

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Abstract

Collaborative research and development (R&D) has been encouraged based on the belief that knowledge spill-over is mutually beneficial for partners. Although the benefits are supported by science and technology policy research, the risk of R&D collaboration has not been extensively discussed. Two independent studies suggest that there are risks associated with the overuse of collaborative research frameworks. Two sets of R&D collaboration data were analyzed: between the national bio-technology research program and 1) Data Envelop Analysis (DEA), and 2) between Stochastic Frontier Analysis (SFA). In the case of SFA, output measures were integrated into a single output, with weights extracted from research programme managers' responses to the questionnaire. While the DEA result demonstrated the inefficiency of collaborative research, SFA did not. Unlike previous research highlighting risks associated with disclosing proprietary R&D and potential conflict of interest, our study indicates that the transaction's social cost affects collaborative research efficiency. Therefore, governments promoting R&D collaborations should be carefully managed, and policy makers must reconsider the strict conditions governing compulsory collaborative R&D programs.

Keywords: Research Collaboration, Efficiency, DEA, SFA, National R&D Program
JEL Classifications: M19, O32

Ⅰ. Introduction

In this study, we aimed to present a balanced view of technological collaborations. Research into this subject has shown a decline in the positive impact of these interactions, as strategic alliances burgeoned in the 1990s (Hagedoorn, 1990; Hagedoorn and Duysters,

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2002; Sakakibara, 1997; Dodgson, 1992a; Powell, Koput and Smith-Doerr, 1996; Gulati, 1998). Technological collaborations are considered most efficient for knowledge diffusion and sharing. Consequently, governments promote collaborative R&D programs to facilitate the smooth linkage between public and private sector research, further highlighting links beyond university – industry interactions. In the private sector, strategic alliances aimed at developing new products are often headlined in newspapers such as the Financial Times and Wall Street Journal. This trend has been reinforced by the thriving network of knowledge society driven by the external economy of sharing knowledge and interchanging information (Castells, 1996).

On the other hand, many studies have identified obstacles that hinder efficient collaborations (Dodgson, 1992b; Kilburn, 1999; Miles, Preece and Baetz, 1999; Hamel, Doz and Prahalad, 1989), however, very few have quantitatively addressed this issue (Miles, Preece and Baetz, 1999; Steensma and Marjorie, 2000; Hwang Jung-Tae and Sa-Gyun Hong, 2010). Therefore, the current study focuses on limitations facing technological collaborations by empirically investigating the efficiencies of collaborative research projects. By comparing the DEA efficiencies of collaborative research projects with those of non-collaborative research projects, this study intends to reveal the hidden risks associated with the collaboration. In addition, the current study adopts DEA assurance region (DEA-AR), and this could alleviate the weakness of DEA - outliner problem. Concerning methodological aspect, we attempt to confirm the result of efficiency analysis by comparing DEA-AR results with SFA.

Ⅱ. Theoretical Background and Research Questions

1. The Rationale for Collaboration

The virtue of technological collaboration is featured in the literature (Hagedoorn and Schakenraad, 1994); Bae Jong-Tae and Jin-Woo Chung, 1997). Governments have initiated the R&D consortia to create a knowledge sharing culture, and their role as a mediator that prevents opportunistic behaviors has been previously highlighted (Sakakibara, 1997). Many studies address the rationale behind establishing collaborations. Technological collaborations are forged for knowledge transfer (Hagedoorn, 1990), complementary asset and resources (Powell, Koput and Smith-Doerr, 1996; Teece, 1992), external economy (Coombs et al., 1996), risk sharing (Jorde and Teece, 1989; Tether, 2002), and shortening time to market (Tether, 2002; Narula, 2004; Uzzi, 1997). It is highly likely that knowledge sharing and spill-over are the major reasons for encouraging public – private partnerships in R&D, while inter-firm collaborations are ascribed to the pressures of rapid product life cycle (Narula, 2004).

2. The Risk Associated with Collaboration

Although collaborative efforts in research and development are highly praised, skeptical air is expressed, based on the psychological tendency of individual researcher (Denning and Yaholkovsky, 2008; Hadjimanolis, 2006; Cramton, 2001). Therefore, a few influential factors controlling the efficiency of scientific and technological research collaborations have been described: 1) personal and organizational. On the personal aspect, these include personal traits and compatibility (Hara et al., 2003). The coordination problem is crucial. Individuals often do not commit to collaborative project. Without well understood rules and coordination processes, the simple information and communication technology- based tools do not work (Weiss and Hughes, 2005; Denning and Yaholkovsky, 2008). The famous prisoner's dilemma illuminates the possible problem lurking beneath technolo- gical collaborations.

Furthermore, collaborations between individuals affiliated with different organizations may add cost. Traditionally, transaction cost approach indicated that inter-organizational costs—communication and opportunistic costs—may surpass internal organizational bureaucratic costs, which leads to vertical integration (Silver, 1984). Intermediate alliances, known as "something between market and hierarchy", can only reduce such inter-organizational costs (Williamson, 1975), but not eliminate them. Competitor participation could result in opportunistic behavior and dampen the positive impact of collaborations (Park and Russo, 1996)

It is also interesting to understand how diverse types of collaborations matter. The literature divides technological collaborations into several categories. In the private sector, inter-organizational relationships are depicted as varying forms of strategic alliances. The proposed framework places the highest level of strategic alliances as equity-based joint ventures and non-equity based outsourcing activities as the lowest (Jorde and Teece, 1989). External linkages have been segregated into horizontal—known as coopetition (Brandenburger and Nalebuff, 1996)—and vertical. It is probable that above mentioned risk factors may present differently according to the type of technological collaboration. Risks associated with strategic alliances can be categorized into relational and performance risks (Das and Teng, 1999). Relational risk is a wide concepts, and individual opportunistic or fair behaviors are addressed separately. In addition, there is the uncertainty issue regarding the availability of appropriate complementary resources, which has been discussed in depth as the uncertainty of organizational fit. Whether it is individual penchant, organizational cost, or inherent risk and uncertainty, collaboration is not the first choice (Hamel, Doz and Prahalad, 1989). Therefore, the virtue of collaborations must be questioned, as to whether the same capable organization performs better on independent or collaborative research projects, rather than comparing an organizations'ability to find cooperative partners or not.

Recently, risk has been discussed in the context of open innovation (Euchner, 2013). Brocke and Lippe (2015) conducted an extensive literature review on managing collaborative R&D projects, and contend that diversity of individual players, uncertainty of working methods and outcomes, difficulty in measuring the performance, and management of creativity with flexible control are major challenges facing collaborative research project managers. However, these risks and negative aspects must be addressed with empirical studies.

3. Collaboration and Performance

Mitchell and Singh (1996) were able to demonstrate how collaborative relationships affect firm survival. Others focused on the aspect of sales and profit growth. Bae Jong-Tae and Jin-Woo Chung (1997) investigated the links between formal/informal technological collaborations for small and medium enterprise (SME) performance, three different performance dimensions were considered: new product innovation, upgrading technological capability, and financial indicators. The size and diversity of formal technological collaborations, and size of informal technological collaborations, may affect all the three performance dimensions positively. Lee Choon-Woo et al. (2001), report two types of partnership-based linkages, venture capital and university research, as significant for firm performance－sales growth.

Lane et al. (2001) studied how the learning capability of joint venture partners affected performance, measured by respondent 5-likert evaluations. Focusing on "absorptive capacity"with sales growth as performance, Kim Young-Joe (2005) investigated the effect of controlling variables of collaborative efforts on firm performance. The result confirmed – previous conclusions by Lane et al., demonstrating that absorptive capacity and collaborative work in tandem positively affect performance. Belderbos et al. (2004) used Community Innovation Survey (CIS) including various types of linkages. In their research, competitor, supplier, customer, university cooperations/spill-overs were questioned with regard to enhancing "value-added per employee" performance. Only one research result indicated no significant performance differences between alliance and non-alliance firms (Miles, Preece and Baetz, 1999). The research suggests that the negative impact of collaborations can be expected if firms are over-dependent on their partners.

In the case of research collaborations in public R&D programs, Grimaldi and Tunzelmann (2002) implemented evaluations from the UK LINK program by including five output factors: Patents, papers (publications), follow ups, commercial exploitation, and matching up. The study revealed the importance of incorporating both qualitative and quantitative aspects.

As the current research focuses on national R&D program, this research extends research results of Grimaldi and Tunzelmann (2002) and Kim Hong-Young and Sun-Yang Chung (2016). This research attempts to utilize more robust and sophisticated methods to evaluate the efficiencies of R&D projects. In addition, as this research takes a cautious approach on collaborative research (emphasizing “the associated risk of collaboration” rather than finding “the rationale for collaboration”), it lies in line with the previous research that emphasized the risk of collaboration (Denning and Yaholkovsky, 2008).

4. Research Questions

Reviewing previous literature highlights two major questions. If technological collaborations are the second choice (Hamel, Doz and Prahalad, 1989), what would occur if we just investigated the efficiency of collaborative research.

Research question:
Does research collaboration improve performance in terms of efficiency?

A hidden research question is a methodological one: whether two different methods DEA and SFA yield the same results. We want to identify the outcome of uniting DEA and SFA, comparing efficiencies of collaborative research projects with those of non-collaborative (stand-alone) research projects.

Ⅲ. Data and Research Methodology

1. Data

The current study adopts two different data sets. A survey conducted by STEPI (www.stepi.re.kr) in 2006, which contains various questions on research projects, such as bottom-up/top-down research program design, collaboration types, and many performance indices. Among 320 research projects, 294 valid responses were used for efficiency calculations. For controlled sample analysis, 99 bio-technology-related projects were originally received, and 93 projects were finally selected after excluding responses without outputs. All research projects mainly belonged to the national research program—government funded—and the area of research was primarily basic and application research.

Sample (projects) selection was both theoretical and pragmatic. The virtue of collaborative R&D was (supposed to be) easily captured in the case of basic/application research and the output index was relatively straight-forward. Collaborative R&D between academics working on scientific knowledge was preferable, as it was relatively free of any conflicting commercial interests. In addition, output measurements were easier for the basic research field, as the papers and patents were more accessible than in the commercial product market.

We identified three input factors, financial investment, length of research project, and the experience of the research project leader. Four output factors were: Number of journal publications (papers), number of patents, number of post-graduates, and number of new members in the newly extended research network. In terms of calculating papers, impact factors were considered. Renowned journals, such as Science, Nature, and Cell received one point, while domestic publication (KCI indexed) were calculated as 0.2. Domestic patents count as 1 and international patent counted as 2. The number of graduates trained through the research project was calculated as 1 for master graduates, and 3 for doctoral graduates. The number of members in the new network was calculated as 1 for international members, and 0.7 for domestic members.[1] All these numbers were later coded into [0,1] range when standardization was required for the analysis with integrated single outputs. The weights were extracted from questionnaire responses of six research program managers, the questionnaire contained both simple questions related to the percentage weights of four outputs, and Analytic Hierarchy Process (AHP) comparisons of the

1) With consultation to anonymous R&D program manager.

four outputs.

2. Model

To analyze the first data set of the national research program, Data Envelopment Analysis (DEA) with assurance region was adopted, for the multi-input and multi-output characteristics of the research projects. Data Envelopment Analysis (DEA) was the main method chosen. According to Zhu (2003), CCR DEA with Assurance Region can be as follows: Input v1, v2 has following ratio of weight, and since multiplying denominator yields,

$L_{1,2} \le \frac{v_2}{v_1} \le U_{1,2}$ thus it can be written as, $L_{1,2}v_1 \le v_2 \le U_{1,2}v_1$

It is possible to build the same constraint condition on outputs with the number of inputs "m" and the number of outputs is "s".

$$v_1 l_{1,i} \le v_i \le v_1 u_{1,i} \qquad (i = 2,\ldots,m) \tag{1}$$

$$u_1 L_{1,r} \le u_r \le u_1 U_{1,r} \qquad (r = 2,\ldots,s) \tag{2}$$

$$\begin{aligned} (AR_0) \quad & \max_{v,u} \quad uy_0 \\ subject\ \ to \quad & vx_0 = 1 \\ & -vX + uY \le 0 \\ & vP \le 0 \\ & uQ \le 0 \\ & v \ge 0,\ \ u \ge 0 \end{aligned} \tag{3}$$

, where

$$P = \begin{bmatrix} l_{12} & -u_{12} & l_{13} & -u_{13} & \cdots & \cdots \\ -1 & 1 & 0 & 0 & \cdots & \cdots \\ 0 & 0 & -1 & 1 & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \end{bmatrix}$$

and Q is in a similar manner to the P matrix.

The automatic calculation of weights on input/output factors (in the case of normal DEA)is attractive but restricting the weight ratio is preferable. To obtain the reference weight ratio, the Analytic Hierarchy Process (AHP) survey was undertaken and the ratio was calculated. AHP weight with ±50% of allowance was set as the assurance region. For example if a paper is twice as important as a patent, then the weigh ratio 2:1 is converted to the assurance region. In this exemplary case, it is given as 1≤ paper/patent ≤ 3.

As for the Stochastic Frontier Analysis (SFA), we used the Cobb–Douglas production function due to:

$$\ln(Y_i) = \beta_0 + \beta_1(COST_i) + \beta_2 \ln(YEAR_i) \cdot$$
$$+ \beta_3 \ln(\mathrm{EXP}(ER_i)) + \delta COLLAB_i + V_i - U_i \tag{4}$$

Here, we can use half normal and truncated models where the collaboration dummy is directly incorporated into the production function. We may use a separate truncated normal model, where U_i can be explained by the collaboration dummy.

$$U_i = \delta_0 + \delta_1 COLLAB_i + u_i \tag{5}$$

Finally, softwares that were used for this research are: DEA-XL was used for DEA assurance region and LIMDEP was used for the SFA.

Ⅳ. Results and Discussion

1. DEA Efficiency of Collaborative R&D [1)]

From 99 valid responses, 93 responses fully contained information on three inputs and four outputs. Focusing on more consistent and similar research projects in the homogeneous field of bio-technology may highlight the comparison results. Table 1. indicates that the performance of collaborative research projects is better in the case of education and networking outputs. However, even in absolute terms, the performance of collaborative research projects is slightly low in journal publication and patents outputs. Stand-alone R&D projects yield more journal publications on average (4.10) than collaborative R&D projects (2.89). This is surprising considering that collaborative research projects have bigger R&D investments (research budget) compared to those performed independently.

Even with large investments and longer research duration, the efficiency of collaborative research may be lower than stand-alone research, which is reflected in our simple statistical analysis (equivalent to one way ANOVA). The final rows of Table 1 contain comparisons of DEA efficiencies. The result shows that the efficiency of collaborative R&D (0.395) is significantly lower than that of other cases (.527). This underperformance of collaborative R&D projects is confirmed in four different DEA efficiency evaluations. DEA was conducted in different ways, we asked R&D program managers about the weight of four output factors: Paper, patent, education, and network. For precision, the Analytic Hierarchy Process (AHP) questionnaire was used in parallel. Since it is possible to standardize each output factor into an 0–1 range, whether raw or standardized values, the simple survey weights on yielding integrated output, or the weights on assurance region (DEA-AR) methods were used, various ways exist for calculating DEA efficiencies of each R&D project. We have selected four kinds of combination: 1) DEA with standardized single output using survey weights, 2) DEA assurance region with multiple input-outputs using survey weights, 3) DEA assurance region with single output using AHP weights, and 4) DEA assurance region with multiple input-output using AHP weights.

The efficiency values ranged from [0,1], which enabled us to implement Tobit regression instead of simple non-parametric comparison of averages. The result of Tobit regression featured in Table 2 reaffirmed that the DEA assurance region method presented significant differences between the collaborative and stand-alone research projects.

2. SFA of Collaborative R&D

1) Majority of this part is presented in other research reports (Hong et al. 2006; Hwang and Hong 2010).

Table 1. Basic Comparison on Efficiency of R&D Collaboration: National Bio-Technology R&D Program Project.

	Contents	Collaborative R&D Projects	Stand Alone R&D Projects	Mahn - Whitney Sig.
Input (Average)	The Number of Projects	47	46	-
	Investment (Million Won)	249	78	.018**
	Duration (Months)	33.9	29.9	.051*
	Projector Leader Experience (Year)	9.9	10.7	.358
Output (Average)	Journal Publication	2.89	4.10	.486
	Patent	0.47	0.73	.078*
	Education (Graduates)	5.13	5.08	.728
	Building Network	8.27	6.83	.764
DEA	DEA Output_using_survey weight	0.237	0.332	.126
	DEA_Normal	0.385	0.468	.094*
	DEA-O_InAR(AHP weighted single output)	0.474	0.663	.000***
	DEA-InOut_AR (survey based AR range)	0.395	0.527	.001***

Note: *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Sources: Modified from Hong Sa-Gyun et al. (2006); Hwang Jung-Tae and Sa-Gyun Hong (2010).

We extended our comparative study with SFA to check whether the DEA result (of negative impact of research collaboration) was robust. The dependent variable was integrated into one single output same as "DEA_OutSurv" using survey weights. Table 3 shows three different models: Half-normal, truncated normal 1, and truncated normal 2. In all three models, the negative impact was not evident as statistically non-significant. We preferred using the truncated-normal model 1 because it takes collaboration dummy as a factor directly affecting production function. The minus value (-0.201) of collaboration efficiency in the truncated normal 1 model was in line with the DEA result, but was far from being statistically significant. This is contrary to our expectation, as we anticipated the

Table 2. Tobit Regression on DEA Efficiencies of R&D Projects.

	Dependent variables			
	(DEA_OutSurv)	(DEA_Norm)	(DEA_OutAHP_InAR)	(DEA_IO_AR_VRS)
Constant	0.332***	0.468***	0.663***	0.527***
COLLAB	-0.096*	-0.083	-0.189***	-0.132***
Log-likelihood	-9.73	-15.39	9.17	23.32

Note: *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

efficiencies from DEA and SFA to be in accordance. Considering the fact that the DEA-using surveys showed very weak arguments of underperforming collaborative research, we caution that such SFA results may originate from "weighting outputs". For example, AHP weights were almost even for the four outputs, with maximum value for "paper" output being 36%, while the maximum of simple survey weight was 61%. However, the SFA remains confusing. By combining the DEA and SFA results, we conclude that research collaboration may reduce research performance, but the hypothesis of underperforming collaborative research remains weakly supported.

Ⅴ. Conclusion

1. Concluding Remark

As we have presented in 〈Table 2〉, the minus coefficients of the variable "COLLAB (collaboration)" highlight the hidden costs and drawbacks in research collaborations. Hence, we conclude by reminding the major research question.

Research question is revisited:
Does research collaboration cause higher performance in terms of efficiency?
Answer: Contrary to expectation, we observed lower performance in general. The absolute performance of research collaborations in national R&D programs is similar between independent (stand alone) and collaborative R&D projects, while investing significantly more resources (inputs) in the latter resulted in lower DEA efficiency scores.

Did DEA and SFA produce the same results?
Answer: No.
DEA produced the result of revealing the inefficiency of collaborative R&D. However, this inefficiency was not proven in the case of SFA, the efficiency gap between collaborative and solo projects is not statistically significant. Unfortunately, DEA-AR was not sufficient to prevent the outliner problem of DEA efficiency evaluation.

Until now, the virtue of research collaboration is so emphasized that the design of national research and development programs endowed strong Incentives for research collaborations between different parties. In certain cases, this research collaboration is compulsory. The definition of collaboration by Schrage (1995)—"the process of shared creation: two or more individuals with complementary skills interacting to create a shared understanding that none had previously possessed or could have come to on their own" (p. 33)—becomes unusual, since the director of small and medium sized research projects could manage the project without help from other parties, but is forced into collaboration. Considering the research collaboration as the second best choice, it is not so surprising that the efficiency is lower.

2. Limitation and Suggestion for Future Research.

Even though we aimed to analyze homogeneous samples, the research that aims to apply patents and technology licensing can be different from more basic biological research. Although, the four quantifiable outputs and three inputs are collected based on interviewing key R&D program managers, it is not an exhaustive list, and further hard to quantify qualitative research project outputs exist. This research is not free from these inherent shortcomings.

In retrospect, it would have been possible to select samples due to the fact that innovators are considered attractive partners for technological collaborations(Hagedoorn and Schakenraad, 1994), thus all firms are not in the same position to benefit from the virtue of technological collaboration (Ahuja, 2000). Therefore, chief scientists of collaborative research projects have strong capabilities and reputations, and thus can offset risk of collaborative research projects. Even though we tried to erase this bias by incorporating "research experience" in the input variables of efficiency evaluation, it could be imperfect. Finally, future research must extend sample size and highlight the limitations of collaborative research in both DEA and SFA methods.

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