Structure, Behavior, Governance and Performance of Clusters-Estimate of Performance by Data Envelopment Analysis

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Abstract

This paper offers an analysis of the structure, behavior of actors, performance, as well as governance system of clusters. It provides application of the methodology of Data Envelopment Analysis (DEA) to examine clusters in Korea. The first application focuses on 12 Regional Research Centers (RRC) formed by Korea Research Fund in ten universities outside Seoul. The second application focuses on research centers based at Pusan National University.

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1. Introduction

Industrial clustering is obviously a form of industrial organization. A cluster or combinations of clusters can be treated as a market. Following the framework of traditional industrial organization theory, this paper will analyze the structure of a cluster, behavior of its actors, and its performance. In addition to these three components, the paper will also analyze the governance system of the cluster.

For the cluster study, this paper suggests a research framework that has no widely received model or a comprehensive framework of analysis. Individual factors and actors in each sector will not be discussed or reviewed in detail in this paper. It offers a new suggestion of grouping factors and actors in cluster analysis.

In the second part of the paper, a new method of data envelopment analysis (DEA) is introduced and used to measure the performance of clusters. The cluster chosen for test is a knowledge-cluster formed as a research center in university in Korea. The regional research centers (RRC) are designated and supported by the agency of the central government. The performance of 10 RRCs in universities in Korea is compared using DEA. As a comparative study, firms associated with research centers in Pusan National University (PNU) are surveyed for the measurement of efficiency of cooperation with research centers in PNU.

2. Structure, Behavior, Performance, and Governance of Clusters

1) Structure

Structure of clusters is studied in various contents and scopes in many countries. Since Porter (1990), Council on Competitiveness in U.S. conducted many cluster researches including reports on five US clusters of Atlanta, Columbus, GA, San Diego, CA, Pittsburgh, PA, Research Triangle Area, NC, and Wichita, KS. (See http://www.compete.org for more details). They use Porter's cluster mapping data, selected input and output measures, and extensive survey and interview instrument in the following areas[2]:

- Economic Performance
- Composition and evolution of the regional economy

[2] Quoted from home page.

- Business and innovation environment
- Competitiveness of selected regional clusters
- Implications for the regional agenda

These reports and output can be rearranged to find the structural factors, and these will be listed below. European cases for cluster study are even more abundant. Cooke (1998, 2000) is one of many leading researchers of European clusters. Cooke and his co-workers group many regions by the characteristics of governance of firm support system and business innovation system. OECD (1999, 2001) also conducts a comprehensive research on clusters and provides rich resources for the restructuring of existing studies. There are studies of clusters of Japan and Korea too. (See Ishikura et al. 2003, for example.)

Structure of cluster can be analyzed in terms of geographic scope, density, breadth, entrance and exit and actors besides firms. Existence of financial intermediaries, incubators, service centers, administrative agency, etc. are other components of a cluster structure.

The evolutionary change of a cluster should be reviewed too. For instance, the life cycle of a cluster is an interesting subject of this study. The role of technology change in the life cycle of a cluster may be the most important aspect to analyze.

Industrial characteristics of clusters and regional characteristics will be the object of analysis as well. By identifying a cluster in terms of structure, it becomes easier to provide more systemic information for further analysis and for policy making.

2) Behavior

Behavior of cluster covers forms and methods of networking and linkage. Industry-university cooperation, joint R&D, joint purchase or sales are objects of behavior too. Research bodies such as university, research institutes and joint lab and the format of cooperation may belong to the behavior category.

The area of behavior of cluster belongs to survey or empirical study. In the case of European clusters, for example, a study group conducted multi-country, multi-region field survey and questionnaire survey of many firms and figured out characteristics of networking and cooperation. (Cooke et al. 2000). An important question is whether the behavior of a firm is different in and out of a cluster.

A long standing question, that goes back to Schumpeter, on the relation between R&D investment for innovation and firm size can also belong to the behavior of cluster. Since technology is changing so fast and competition is becoming severe, industrial characteristics rather than size of firms may be more important in determining R&D investment for innovation. Furthermore many countries and EU implement RIS policies and cluster policies to help small and medium firms facilitate R&D functions, which SMEs cannot afford otherwise.

Enright (2000) summarizes many characteristics of cluster activities very precisely. Regional characteristics of cluster activities (behavior) can be gathered from papers or reports so as to figure out commonalities and differences.

3) Performance

Performance of cluster deals with the outcome of cluster activities. Like an ordinary industrial organization, the outcome should be measured by sales, profit, market-share, and not only by their levels but also by the speed of change in these respects for individual firms and for a cluster as a whole. For the longer time span, number of innovation activities which could be measured by patents, R&D investment, number of industry-university cooperation, etc., can also be considered.

Measurement of performance is a difficult part of cluster study. Separating the contribution of cluster on individual firm's performance from that of the region is not easy. If a region is relatively small and has one cluster for development purpose, the growth accounting method can be used to measure the performance of the cluster. However if a region is large and possesses many clusters and other institutions and systems, the measurement of performance of individual clusters and institutions is very difficult. In addition, if a support policy is conducted which influences actors in a cluster or clusters throughout many regions, it is even more difficult to measure the performance. Firms, which are the most important actors in a cluster, are reluctant to reveal their financial information. A nonparametric estimation method, namely Data Envelopment Analysis (DEA) is introduced for this purpose and is put to empirical use in the second half of this paper.

4) Governance

Governance of a cluster also is an important component. Central and local governments, associations, cooperatives or unions are also objects of analysis.

Such characteristics of these institutions whether as private oriented, government sponsored, or as public sector oriented, are related to the role of industrial policy. The financial resources of those institutions, such as membership dues, subsidies, public loans and matching fund constitute another characteristic to be considered. Cluster policies of government, in both central and regional level, comprise another important factor.

The governance part deals with an institutional aspect of the cluster system. The role of many agencies and institutions mentioned above for the success of a cluster is another important aspect to figure out. As a cluster is formed more or less by government policy, the inception and operation afterwards tend to be influenced by the governance system. Measuring the performance of the governance system is even more difficult. A hypothesis in this regard may be that bureaucracy may make the governance system more costly for success. The case of Tama (Ishikura et al., 2003) provides a good example of private sector initiated governance system. If the Tama cluster becomes more successful, its governance system may emerge as a new model for a private sector oriented cluster formation.

3. Performance Analysis of Regional Research Center in Korea by DEA

As mentioned above, in this part of the paper, we use a new method to measure the performance of clusters. In particular, the method is used to measure the performance of regional research centers in Korea.

1) Regional Research Center(RRC)

In order to improve local universities' research abilities and to help R&D function of SMEs, Korea Research Fund designated 12 RRCs in ten universities located in areas other than the capital city, Seoul. Each center is earmarked for specialization and promotion of a specific technology. For example, RRC in Pusan National University is assigned environmental engineering technology. RRCs are supported and financed for 9 years in training MA and Ph.D students, in publishing academic papers, and in carrying out R&D cooperation, such as patenting, product development, and technology transfer with associated firms.

Table 1: Input for RRC Program (1996-2000)

(Unit: person, million won)

Univ.	Research Personnel				R&D investment				
	Professor (x1)	Ph. D. researcher (x2)	MA researcher (x3)	Total researcher (x4)	Total (x5)	Science Foundation (x6)	Regional Gov't (x7)	Firm (x8)	Univ (x9)
In ha	17	14	32	125	1,366.0	474.0	300.0	189.0	403.0
Gye myung	17	8	19	78	3,142.8	433.8	361.5	142.5	2,205.0
Kyung sang	35	13	45	111	971.3	471.3	160.0	165.5	174.5
Han yang	17	21	41	85	1,912.5	493.5	267.25	653.0	498.8
Chung nam	18	21	70	112	1,134.0	466.8	366.5	277.0	23.8
Ho seo	22	5	30	78	1,440.0	449.8	177.5	630.3	182.5
Chung buk	18	28	54	132	1,157.0	485.0	170.0	259.0	243.0
Che ju	24	5	24	67	671.0	406.0	92.5	89.0	83.5
Young nam	36	22	53	161	1,695.8	452.0	175.0	346.8	722.0
PNU	36	29	65	146	1,646.8	526.0	200.0	603.3	317.5

Inputs for RRC program are measured in terms of research personnel (number of professors, Ph. D. and MA level researchers) and R&D related investment (from Korea Science Foundation, regional government, universities, and cooperating firms) (Table 1). Outputs of RRC are measured by academic outcome (production of Ph. D. and MA degree holders and publication of research papers) and technological outcome (technology transfer, number of patent and number of product development)(Table 2).

The reason for selecting RRC as a prototype of knowledge cluster is threefold. First, they are homogenous entities established by the same policy and operation system. Second, all the centers use the same input variables. Third, in terms of production function they have homogenous factors of production.

Table 2: Output of RRC program 1996-2000

(Unit: person, each)

Univ	Academic outcome		Technological outcome		
	Production of specialist (y1)	Research paper (y2)	Technology transfer (y3)	Patent (y4)	Product development (y5)
In ha	27.6	91.6	4.4	1.20	1.0
Gye myung	11.8	58.4	15.8	2.42	10.0
Kyung sang	35.2	89.6	10.0	2.09	6.0
Han Yang	24.6	91.8	20.4	7.89	9.0
Chung nam	28.2	72.2	8.0	0.00	6.6
Ho seo	11.8	77.6	19.4	1.40	9.8
Chung buk	61.4	161.8	2.8	5.19	2.2
Che ju	14.4	920	10.5	1.20	4.0
Young nam	23.8	234.8	14.2	6.19	6.8
PNU	41.4	189.4	16.6	5.32	3.8

2) Data Envelopment Analysis (DEA)[3]

(1) Model of Efficiency Measure for RIS

We use a nonparametric approach to measure the efficiency and performance of a firm's technical effort.[4] We try to identify the extent of the growth of many firms (cities) which can be explained by differences in efficiency and its components, i.e., scale and congestion. We outline the model designed to measure the efficiency of each firm in cluster. Economists typically think of firms or decision making units as optimizing. The firms are assumed to have a goal and to make production choices to do the best they can in achieving the goal given the technology constraints.

The efficiency measures we discuss here are essentially consistent with the goal. The first step of the efficiency model is to compute the DEA-based efficiency measures using the inputs and outputs identified in a cluster. We will show the DEA formulation and its decomposition into various sources of

[3] This part of the paper is drawn from Lim (2005)

[4] Inefficiency (technical inefficiency) is said to be present when the evidence shows that it is possible to improve some input or output without worsening some other input or output.

efficiency/inefficiency. The issue here is to determine the extent to which these sources are responsible for the change in growth (or performance) of firms (or cities)

(2) Efficiency and DEA

We define efficiency as the ability to produce the outputs or services with a minimum resource level. Farrell (1957) recognizes the importance of measuring the extent to which outputs can be increased through higher efficiency without using additional resources (inputs). Efficiency in production is defined in terms of Pareto optimality. The condition of Pareto optimality states that a decision-making unit (DMU) is efficient if an output cannot be increased without increasing any of the inputs and without decreasing any other output. A DMU is not efficient if an input can be decreased without decreasing any of the outputs and without increasing any other input. DEA was initially used to measure the relative efficiency of non-profit organizations. However, the application of the method has quickly spread to profit-making organizations.

DEA is a non-parametric linear programming technique that computes a comparative ratio of outputs to inputs for each unit, which is considered as the relative efficiency. An advantage of DEA is that no preconceived functional form is imposed on the data in determining the efficient units. DEA estimates the production function of efficient DMUs using piecewise linear programming on the sample data instead of making restrictive assumptions about the underlying production technology. The importance of this feature here is that a firm (a city)'s efficiency can be assessed based on other observed performance. DEA identifies the inefficiency in a particular DMU by comparing it to similar DMUs regarded as efficient, rather than by trying to associate a DMU's performance with statistical averages that may not be applicable to the DMU.

The principal disadvantage of DEA is that it assumes the number of physical units included and other data to be free of measurement error. While the need for reliable data is the same for all statistical analysis, DEA is particularly sensitive to unreliable data because the efficient units determine the efficient frontier and, thus the efficiency values of those units under this frontier. This potential problem with DEA is addressed through stochastic DEA designed to account for random disturbances.

(3) The DEA Formulation

In our model, we suppose that there are $x^k = (x_{k1},\cdots, x_{kn})$ inputs and $y^k= (y_{k1}, \cdots, y_{kn})$ outputs for k=1, ⋯, K. These may be of the same firm over the K different periods or K firms in the same period or a set of panel data. Nonparametric frontier technology formed by these DMUs may be written as

$$T = \{(x, y): \sum_{k=1}^{K} z_k y_{km} \geq y_m, m = 1,\ldots, M, \sum_{k=1}^{K} z_k x_{kn} \leq x_n, n = 1,\ldots, N, z_k \geq 0, k = 1,\ldots, K\} \tag{1}$$

where $z=(z_1,\cdots,z_k)$ denotes the vector of intensities that form the smallest convex hull of the observed input and outputs vectors. T is the convex hull closure of the absorbed data (x^k, y^k). The reference technology exhibits constant returns to scale (CRS). By adding restrictions on the intensity variables, *z*, reference technologies that form nonincreasing returns to scale (NIRS) or variable returns to scale (VRS) can be formed (Fare et al., 1994).

In order to measure Farrell's technical efficiency, we first construct the following linear programming problem for DMUs k, k=1,⋯, K.

$$\begin{aligned} & F_i(x^k, y^k) = \min \quad \mu \\ & s.t. \sum_{k=1}^{K} z_k y_{km} \geq y_m, m = 1,\ldots, M, \\ & \sum_{k=1}^{K} z_k x_{kn} \leq \mu x_n, n = 1,\ldots, N, \\ & z_k \geq 0, k = 1,\ldots, K\} \end{aligned} \tag{2}$$

For each DMU, $F_i(x^k, y^k)$ is Farrell input measure of technical efficiency relative to the reference technology T. Since each firm's specific input-output vector (x^k, y^k) belongs to the reference technology T, $F_i(x^k, y^k) \leq 1$, and efficiency is expressed by $F_i(x^k, y^k)=1$. The primary advantage of using the non-parametric DEA approach compared with traditional parametric (e.g. Cobb-Douglas) counterpart is that modeling the relationship between the inputs and outputs does not require assignment of predetermined weights. Rather, these intensity vectors (z_k, k = 1,⋯,K) vary with each observation since each DMU is compared separately against the best practice where their magnitudes are determined optimally for each DEA formulation. Furthermore, the optimal value of technical efficiency, μ, is independent of the differences in the units of measurement of the inputs and the outputs.

(4) Decomposing Technical Efficiency

Two sources of inefficiency are those associated with the type of disposability and the returns to scale exhibited by underlying production functions. Weak disposability (WD) indicates the presence of congestion, whereas strong disposability (SD) is an indication of absence of congestion[5]. Evidence of congestion is present when reductions in one or more inputs can be associated with increases in one or more outputs - or, proceeding in reverse, when increases in one or more inputs can be associated with decreases in one or more outputs - without worsening any other input or output. Congestion presents when increase in inputs results in output reduction[6]. Inefficiency arises from the fact that it is not costless to dispose of unwanted inputs or outputs. As a result, additional resources must be devoted to such disposal that would otherwise be used towards the production of the desired outputs. Therefore, the issue of whether the sector in question exhibits strong or weak disposability becomes crucial in the analysis of sectoral efficiency.

Furthermore, it is not clear *a priori* whether the movement of a DMU towards the best-practice frontier is due to increasing efficiency in the use of existing

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[5] Strong disposability is defined as $\forall x \geq \hat{x} \in L(y \mid C, S)$ implies that. $x \in L(y \mid C, S)$ That is, it represents that if inputs are either kept the same or increased, output will not decrease. Strong disposability of inputs means that an increase in inputs cannot decrease i.e., congest output. Congestion here implies that there is too much input. Weak disposability of inputs can be used to allow for the possibility of congestion $\forall x \in L(y \mid C, W)\, and\ \lambda \geq 1$ Imply $\lambda x \in L(y \mid C, W)$.

[6] The definition is restricted to technical aspects of inefficiency and do not require prices or other value units to determine a worsening or an improvement. It refers to what might be called waste in the sense that it represents an unnecessary expenditure of resources for inputs. The resource expenditures could have been avoided without having hat to augment other inputs or reduce any outputs.

resources or can be attributed to a change in size, the returns to scale. The issue here is to determine the direction of the changed pattern of the resources, i.e. the change in output generated by a given change in inputs. For these purpose, constant returns to scale, CRS, are said to occur when inputs and outputs change at the same rate. On the other hand, variable returns to scale, VRS, are to occur when inputs and outputs change at a different rate.

Our final aim is to decompose the technical efficiency of each cluster under CRS and SD, into the product of three components. One component (Scale) measures the deviation away from the CRS assumption. Another (Congestion) measures the deviation of each cluster away from the SD assumption. Residual, pure technical efficiency represents the unexplained deviation of each DMU away from the best-practice frontier.

For scale efficiency, we need an input efficiency under a variable returns technology, L(y | V, S)[7] and a constant returns technology, L(y | C, S). Input measure of Farrell's technical efficiency under a variable returns technology is defined as follow

$$F_i\ (y, x \mid V, S) = \min\{\ \lambda : \lambda x \in L(y \mid V, S)\} \quad (3)$$

where the technology satisfies variable returns to scale (V) and strong disposability (S) of inputs. As scale efficiency is defined as a relative ratio between L(y | V, S) and L(y | C, S), Input scale efficiency is measured as

$$S_i\ (y, x \mid S) = F_i\ (y, x \mid C, S) \,/\, F_i\ (y, x \mid V, S) \quad (4)$$

$S_i\ (y, x \mid S)$ <1, which means scale inefficiency, is due to increasing returns to scale (IRS) if $F_i\ (y, x \mid N, S) = F_i\ (y, x \mid C, S)$, and decreasing returns to scale (DRS) if $F_i\ (y, x \mid N, S) > F_i\ (y, x \mid C, S)$ [8]. In order to isolate

[7] V indicates VRS, and C dote CRS under strong disposability (S).

[8] (y, x|N, S) is input technical efficiency under nonincreasing returns to scale (NIRS).

congestion from technical efficiency, we need to compute the following additional input measure.

$$F_i\ (y, x \mid V, W) = \min\{\ \lambda x \in L(y \mid V, W)\} \tag{5}$$

where the technology satisfies variable returns to scale (V) and weak disposability of inputs (W). Input congestion measure is defined as

$$CN_i(y, x \mid V) = F_i\ (y, x \mid V, S) / F_i\ (y, x \mid V, W) \tag{6}$$

We say that an observation k is congestion free if $CN_i(y, x \mid V) = 1$, and that it is congesting if the measure is less than one. Finally, combining scale efficiency and congestion in (4) and (6), the decomposition of input measure of technical efficiency is derived as

$$F_i\ (y, x \mid C, S) = S_i\ (y, x \mid S) \cdot CN_i(y, x \mid V) \cdot F_i\ (y, x \mid V, W) \tag{7}$$

In this way, the original technical efficiency measure, $F_i(y, x \mid C, S)$ is decomposed into three components: namely scale, congestion and residual or pure technical inefficiencies. The first component measures deviations from CRS, the second captures deviations from strong disposability (SD) of inputs, and the third is a measure of input technical efficiency measured relative to a VRS technology with weak disposability.

3) Results from DEA Analysis

Table 3 shows the outcome of DEA and compares the relative efficiency of ten RRCs. If the coefficient is equal to 1 or closer to 1 that means the efficiency of that institute is higher and vice versa.

Table 3: Input and Output Summary

(Units: number, million Won)

Univ.	In ha	Gye myung	Kyung sang	Han yang	Chung nam	Ho seo	Chung buk	Che ju	Young nam	PNU
Overall	0.36	0.74	0.61	0.87	0.51	1.00	0.61	0.66	0.61	0.68
Production of specialist	27.60	11.80	35.20	24.60	28.20	11.80	61.40	14.40	23.80	41.40
Research paper	91.60	58.40	89.60	91.80	72.20	77.60	161.80	92.00	234.80	189.40
Total researcher	77.00	78.00	111.00	85.00	112.00	78.00	132.00	67.00	161.00	146.00
R&D investment	1,366.20	3,142.80	971.30	1,912.50	1,134.00	144.00	1,157.00	671.00	1,695.80	1,646.80
Academic outcome	0.60	0.76	0.80	0.81	0.77	1.00	0.83	0.82	0.73	0.89
Technology transfer	4.40	15.80	10.00	20.40	8.00	19.40	2.80	10.50	14.20	16.60
Patent	1.20	2.42	2.09	7.89	0.00	1.40	5.19	1.20	6.19	5.32
Product development	1.00	10.00	6.00	9.00	6.60	9.80	2.20	4.00	6.80	3.80
Total researcher	125.00	78.00	111.00	85.00	112.00	78.00	132.00	67.00	161.00	146.00
R&D investment	1,366.20	3,142.80	971.30	1,912.50	1,134.00	144.00	1,157.00	671.00	1,695.80	1,646.80
Technology outcome	0.12	0.71	0.41	0.93	0.25	1.00	0.38	0.49	0.49	0.46

Two important findings from the DEA of 10 RRCs are the following. First, the performance of a RRC does not coincide with the reputation of the institute, such as a big national university or a big private university with high recognition. Second, relative efficiency is not directly related to the scale and investment. Even though DEA has weak points, the exercise above shows that the DEA model can be used for evaluating the performance of clusters and other institutes.

4. Performance Analysis of Membership firms of Research Centers in Pusan National University

There are many research centers in PNU as shown in Table 4. Each center has its own associated or member firms for research and development and other forms of cooperation. Questionnaire on the performance of pre-and post cooperation were distributed and 30 of them retrieved. Characteristics of the sample are summarized in Table 4.

Table 4: Characteristics of the Survey Sample (30)

Centers	Regional Research Center (14), Engineering Research Center (8), Technology Innovation Center (3), Science Research Center (3), Others (2)
Industry	Machine and parts (7), Chemical (5), Auto parts (5), Fabricated metal (4), Iron and steel (4), Rubber and plastic (3), Leather products (1), Others (1)
Average Cooperation period	2. 4 years
Average Cooperation per firm	1.5
Average Program cost	82 million Won

Five types of research centers are involved and industrial characteristics vary widely. The average cooperation period of firms with centers is 2.4 years, and the average number of cooperation per firm with the centers is 1.5. The average cost of cooperation was estimated to be 82 million Won.

Table 5 shows pre- and post-cooperation efficiency by DEA. The opportunity cost is estimated as the product of difference in efficiency times the sales amount after cooperation in million Won. The findings from this estimation are threefold. The first finding is that 11 out of 30 surveyed firms showed increase in efficiency after cooperation with the centers. This means only about one third of associated firms experienced the advantage of cooperation. The second point is that the average efficiency measurement turned out to be negative in terms of opportunity cost. Finally, the reliability of data is to be checked again before reaching a final conclusion. Nevertheless, the effect of cooperation would be smaller than expected in the short run.

Table 5: Pre- and Post-Cooperation Efficiency

DMU	Pre Coop	Post Coop	Difference	Opportunity cost
1	0.15	0.17	0.02	11.24
2	0.25	0.22	-0.03	-184.05
3	0.28	0.17	-0.11	-47.652
4	0.20	0.19	-0.01	-15.96
5	0.35	0.56	0.21	2945.73
6	0.21	0.28	0.07	82.38
7	0.43	0.38	-0.05	-382.00
8	0.11	0.05	-0.06	-12.11
9	0.00	0.22	0.22	282.76
10	0.04	0.05	0.01	1.02
11	0.19	0.19	0.00	0.00
12	1.00	0.69	-0.31	-16943.20
13	0.41	0.50	0.09	4495.99
14	0.02	0.02	0.00	0.00
15	0.19	0.14	-0.05	-66.30
16	0.51	0.47	-0.04	-437.62
17	0.60	0.84	0.24	2062.98
18	0.22	0.19	-0.03	-46.01
19	0.88	1.00	0.12	1173.93
20	0.97	1.00	0.03	4191.10
21	0.35	0.32	-0.03	-279.45
22	0.98	0.66	-0.32	-44237.50
23	0.52	0.42	-0.10	-2663.37
24	0.24	0.19	-0.05	-102.25
25	0.60	0.41	-0.19	-2475.91
26	0.45	0.35	-0.10	-900.62
27	0.58	0.37	-0.21	-15169.80
28	0.46	0.41	-0.05	-124.983
29	0.48	0.26	-0.22	-1178.96
30	0.81	0.55	-0.26	-4266.6
Average	0.41	0.37	-0.04	-2476.24

To find the effect of cooperation by the characteristics of associated firms, size and distance from the center is taken into account. Table 6 shows that in the case of 30 employees or less, the relative efficiency turned out to be positive but in the case of more than 30, the opportunity cost is negative. Since the major form of cooperation is R&D function, smaller firms which have no R&D function inside may have more benefits of cooperation. More firm conclusion could be derived if the sample size was larger.

Table 6: Relative Efficiency by Size

size	Pre-Coop	Post-Coop	Difference	Opportunity Cost
30 and less	0.25	0.26	0.01	143.00
Over 30	0.56	0.47	-0.09	-5093.97

Cluster studies emphasizes that the distance matters (Acs 2000). In our case, however, the firms' location from centers had no real impact on efficiency. This can be seen from data presented in Table 7. Again data from larger sample are required for a more decisive conclusion.

Table 7: Relative Efficiency by Distance from Center

Distance	Pre-Coop	Post-Coop	Difference	Opportunity cost
5Km	0.19	0.13	-0.06	-25.24
5~10Km	0.46	0.35	-0.11	-10416.30
10~15Km	0.21	0.29	0.08	560.42
15~20Km	0.60	0.55	-0.05	-1595.21
20Km or over	0.39	0.32	-0.07	-947.16

As introduced in DEA, scale efficiency is defined as the ratio between technical efficiency and pure technical efficiency (Sharma et. al., 1997). That is

$$SE=TE(CRS)/TE(VRS)$$

Pure technical efficiency estimates the degree of approach of individual DMU to the efficient frontier. Scale efficiency estimates the degree of approach of individual DMU to scale economy.

Table 8: Pure Technical Efficiency and Scale Efficiency

DMU	Technical Efficiency	Pure Technical Efficiency	Scale Efficiency
1	0.154	0.868	0.177
2	0.186	0.232	0.801
3	0.176	1.000	0.176
4	0.204	0.424	0.481
5	0.552	0.678	0.814
6	0.104	0.732	0.142
7	0.352	0.412	0.854
8	0.052	0.652	0.079
9	0.040	0.386	0.103
10	0.028	0.950	0.029
11	0.166	0.474	0.350
12	0.680	0.696	0.977
13	0.470	0.500	0.940
14	0.022	0.462	0.047
15	0.152	0.334	0.455
16	0.374	0.428	0.873
17	0.656	0.774	0.847
18	0.120	0.440	0.272
19	0.844	0.950	0.888
20	0.976	1.000	0.976
21	0.290	0.322	0.900
22	0.674	0.854	0.789
23	0.446	0.556	0.802
24	0.198	0.366	0.540
25	0.438	0.510	0.858
26	0.356	0.394	0.903
27	0.458	0.552	0.829
28	0.432	0.734	0.588
29	0.478	0.726	0.658
30	0.820	0.846	0.969
평균	0.363	0.608	0.597

The finding from this paper's analysis does not indicate significant scale efficiency. That is, pure technical efficiency is not very large on average compared to technical efficiency represented by constant returns to scale. Another finding is that the average technical efficiency is low in most cooperating firms. A similar result is reported in the case of Southeast Korea based on a survey that shows that firms implementing innovation activity showed no innovation activity (Kang et. al., 2004).

5. Conclusion

This paper has two parts. The first part argues that the analysis of industrial organization can be applied to the analysis of clusters. That is, structure, behavior (activity), and performance can be used for modeling and analyzing clusters. As a fourth factor, governance of supporting or operating system of cluster can also be included in the analysis. The second part of the paper presents an actual application. Since it is difficult to acquire micro data on clusters, the DEA method is employed as an estimation tool. An application of DEA on RRCs in Korea and associated firms of research centers in Pusan National University is reported. Because of sample size, firm conclusions are hard to make. Some observations that can be made are as fallows. First, the size of firms may matter for efficiency related to cooperation with research centers. Second, the effect of cluster may appear to be adverse in the short run. This may suggest that R&D cooperation needs longer time to yield a visible effect.

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