R&D productivity and the organization of cluster policy: An empirical evaluation of the Industrial Cluster Project in Japan

Junichi Nishimura[a] and Hiroyuki Okamuro[a*]

[a] *Hitotsubashi University, Graduate School of Economics, Naka 2-1, Kunitachi, Tokyo 186-8601, Japan*

* Corresponding author: Tel.: +81-42-5808792; fax: +81-42-5808882;

e-mail: okamuro@econ.hit-u.ac.jp

Abstract

Industrial clusters have attracted increasing attention as important locations of innovation. Therefore, several countries have started promotion policies for industrial clusters. However, there are few empirical studies on cluster policies. This paper examines the effects of the "Industrial Cluster Project" (ICP) in Japan on the R&D productivity of participants, using a unique dataset of 229 small firms, and discusses the conditions necessary for the effective organization of cluster policies. Different from former policy approaches, the ICP aims at building collaborative networks between universities and industries and supports the autonomous development of existing regional industries without direct intervention in the clustering process. Thus far, the ICP is similar to indirect support systems adopted by successful European clusters. Our estimation results suggest that participation in the cluster project alone does not affect R&D productivity. Moreover, research collaboration with a partner in the same cluster region decreases R&D productivity both in terms of the quantity and quality of patents. Therefore, in order to improve the R&D efficiency of local firms, it is also important to construct wide-range collaborative networks within and beyond the clusters, although most clusters focus on the network at a narrowly defined local level. However, cluster participants apply for more patents than others without reducing patent quality when they collaborate with national universities in the same cluster region.

Keywords: Industrial cluster; University-industry partnership; Small and medium enterprise; R&D; Patent

JEL Classification Codes: O23, O32, O38, R38

1. Introduction

Industrial clusters have recently been recognized as important locations of innovation. They are expected to promote innovation by local firms through the facilitation of inter-firm collaboration and university-industry partnership (hereafter UIP). Thus, policymakers in various countries launched their cluster policies in the 1990s (see Table 1 for details). In their R&D supports, the common purpose is to find technological seeds and bring products into the market, thus cluster policies do not only support the early stage of research, but also the development stage.

[Insert Table 1 here]

However, to the best of our knowledge, there exist few empirical studies on the effects of cluster policies on the R&D performance of local firms. Moreover, the conditions necessary for successfully organizing cluster policies in terms of the R&D performance of local firms still remain an open question.

In Japan, the Ministry of Economy, Trade and Industry (hereafter METI) launched the "Industrial Cluster Project" (hereafter ICP) in 2001. This paper aims to evaluate this cluster policy in terms of R&D performance, using original survey data of small and medium enterprises (hereafter SMEs). We use the number of patent applications, claims, and forward citations as the measures of R&D performance of the firms participating in the UIP, examine the effect of the participation in the ICP on the patent productivity of UIP firms, and discuss the conditions necessary for the effective organization of cluster policies for improving R&D performance.

As indicated in the previous papers, there are different ways to construct the typologies of geographical concentrations of firms and supporting agencies. However, no general consensus has been achieved yet on the spatial, technological, and industrial structure as well as the institutional characteristics of industrial clusters (McDonald et al. 2006)[1]. Thus, the concept of industrial clusters remains quite ambiguous in the related

[1] For example, Cooke (2002) indicates that local learning is crucial in defining a cluster, while other researchers regard effective links between the market processes and the institutional and cultural factors (social capital) as being central (Dei Ottati 2002). The variety of organizations and competitive or

literature. In this study, we will not go into further details of cluster typologies and examine the industrial clusters (regional cluster projects) as defined in the ICP.

Cluster policies can be regarded as regional, industrial, or technological policies and implemented as targeted subsidization or networking support under any of these aspects. Several scholars have recently been opposing to the targeted subsidization of particular regions, industries, and technological fields, arguing that there are no reasons to believe that policymakers are better informed than managers of local firms in evaluating the future economic potentials of the targets (Cowling et al. 1999; Hospers et al. 2009). This discussion is consistent with the public choice theory, which considers government failure to be as common as market failure because of massive information asymmetries and the arbitrary behavior of politicians and bureaucrats (Wolf 1993). As Michael Porter discusses in his work, the cluster policy should aim at "removing obstacles, relaxing constraints, and eliminating inefficiencies that impede productivity and innovation in the cluster" (Porter 2000).

Regional innovation systems have attracted many researchers (e.g., Abramo et al. 2009; Acs et al. 2002; Aldieri and Cincera 2009; Anselin et al. 1997; Audretsch et al. 2005; Dahl and Pedersen 2004; Fritsch and Franke 2003; Furman et al. 2006; Jaffe et al. 1993; Owen-Smith and Powell 2004; Rondé and Hussler 2005; Squicciarini 2008). Many previous studies have arrived at the general consensus that geography matters in determining the innovative capability of an economy.

Knowledge spillovers beyond the boundaries of organizations are important for clusters to play a significant role in promoting innovations. Knowledge flow is increased by the diversity of organizations and people (Fujita 2007). Knowledge may flow among firms as well as between firms and research institutes including universities. Knowledge flow in the network of universities and local firms is particularly important in the ICP, because it includes the regional clusters of science-based industries such as biotechnology and information technology (IT), for which the link between science and technology, thus between universities and firms, is of crucial importance (Gemba et al. 2005). Though it is difficult to measure knowledge flow quantitatively, we have an advantage in this regard, because our questionnaire data include information on the

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cooperative structures in industrial clusters is also considered in constructing a multitude of typologies (Paniccia 1998).

contents of UIPs, such as the types and locations of the partners. This is the major reason of focusing on the firms with UIPs in this paper.

Our sample comprises 229 R&D-intensive SMEs with up to 300 employees that had been engaged in UIP from 2002 to 2004. Among these 229 firms, we identify 57 participants in regional cluster projects. Furthermore, we check for the possibility of a sampling bias between the treatment group (participants) and the control group (non-participants).

We use the number of patent applications, claims, and forward citations from 2003 to 2005 as the proxies for innovation counts by firms. Patent indicators are often used as the proxies for R&D outcomes by UIPs (George et al. 2002; Kim et al. 2005; Motohashi 2005; Lööf and Broström 2008) and in the assessment of public projects (Branstetter and Sakakibara 2002; Darby et al. 2008; Kodama 2008; Okada and Kushi 2004). In the econometric analysis, we use negative binomial (NB), instrumental variables (IV), and treatment effect (TE) regressions in order to cope with the potential endogeneity problem of the participation in the cluster project.

Our main results show that the number of UIP projects increases R&D productivity, while the participation in regional cluster projects as such does not affect it. Rather, collaboration with distant partners enhances both the quantity and quality of applied patents. However, participants in regional clusters tend to apply for more patents than others when they collaborate with national universities within the same cluster regions.

The remainder of this paper is organized as follows. Section 2 provides an overview of the ICP. Section 3 explains our hypotheses based on the concepts of the spatial economic theory, the nature of innovation process, and the market and knowledge-specific failures. In Section 4, we present our data construction and the basic statistics of the treatment and the control groups. Section 5 discusses analytical models. Section 6 provides estimation results. We conclude our study in Section 7.

2. Overview of the ICP

2.1. Basic information on the ICP

METI started the ICP in 2001[2]; the ICP aims at the self-sustaining development of the local economy. METI (2005, p. 17) defines an industrial cluster "not as a mere agglomeration of companies etc. without interactions, but as an innovative business environment where new firms sharing business resources with each other are created one after another through horizontal networks such as industry-academia-government collaboration and inter-firm collaboration, and the resulting state in which industries with comparative advantage play a central role in promoting industrial agglomeration." The intention of the industrial cluster policy can be defined as "to form industry-academia-government networks and industry-industry networks throughout our country for the purpose of forming industrial clusters, and to create new industries and businesses by promoting regional innovation" (*ibid.*).

To achieve this objective, METI provides the following six types of supports (see METI (2005) for further details): (1) network formation, (2) R&D support, (3) business start-up support, (4) marketing support, (5) management support, and (6) fostering human resources. With regard to network formation, which is emphasized in METI (2005), METI dispatches coordinators and advisors to participating firms and universities, holds meetings, seminars, and symposia to promote UIP, and develops and provides databases on firms, researchers, and supporters via websites. Eventually, METI created regional networks between 6,100 firms and 250 universities by 2005 (METI 2006). These network supports are not necessarily concentrated on a particular phase (such as early stage) or type (such as basic research) of R&D projects.

Concerning R&D support, METI supports both the early and late stages of R&D projects, which is in line with the recent cluster policies in the European countries (Table 1). The project report by METI remarks that "consistent support is provided from the time when technological seeds are found through the time when the technologies are put into practical and commercial use" (METI, 2006, p.22).

The ICP particularly aims at building collaborative networks among local SMEs and core national universities in the same cluster regions. SMEs have limited business resources, and the UIP provides them with the opportunity to mitigate this problem. However, it is usually difficult for them to find appropriate research partners; thus, the

[2] The Ministry of Education, Culture, Sports, Science and Technology (MEXT) also started the "Knowledge Cluster Initiative" in 2002. METI cooperates with MEXT in the cluster project.

cluster project is expected to support local SMEs in finding and selecting optimal partners within the cluster. For this reason, we focus on SMEs in the empirical analysis.

The ICP does not exclude large firms, but rather invites them to participate in the regional cluster projects as the core firms in regional R&D networks. However, large firms with global R&D strategy, such as the “big pharma”, are in general not interested in the regional cluster projects because they are more interested in global rather than regional networks and can build their R&D networks without public support, and the scale of public support is usually too small for them. Therefore, in fact, participants of the ICP are mostly SMEs.

Nineteen regional clusters were supported by METI between 2001 and 2005. Appendix 1 shows the characteristics of each cluster such as technological fields, the structure of participants (firms, universities, public research institutes, incubators, and financial institutions), budgets, and cluster areas. Concerning the participants, the “Project to Create Manufacturing Industry in Tokai Regions” involves the largest number of participants. The number of participating universities and public research institutes as well as the budget size is relatively larger in high-tech clusters such as the “Bio Five-Star Company & Tissue Engineering Project” and the “Kyushu Silicon Cluster Project.” The number of incubators is relatively larger in the IT and biotechnology clusters that focus on startup support. Each region has its own comparative advantage, which METI takes into consideration when supporting regional clusters.

METI has finished the first project period (2001–2005) and is currently engaged in the second period (2006–2010) that includes 17 regional clusters. On the whole, METI invested approximately 110 billion yen in the project during the first period. After assessing the outcomes of each regional project considering costs and benefits (network formation, R&D outputs, and the influence on the regional economy), some of the clusters in the first period were merged with other clusters or abolished, and thus disappeared in the second period. Our analysis focuses on the R&D efficiency of the UIP in the first period because it is difficult to analyze the effect of the on-going project and the R&D outputs are more clearly assessed than the overall effects of the ICP.

2.2. Specific characteristics of the ICP

From the comparative perspective, the ICP has some characteristics that researchers should focus on. First, its policy approach is in contrast with the former promotion policies of regional innovation based on the "Technopolis Law" (1983) and the "Brain Location Law" (1988), for example. While these policies aimed at deliberate generation and promotion of new high-tech clusters, the ICP supports autonomous development of existing regional industries without direct intervention in the clustering process.

Second, through the ICP, METI mainly supports network formation (including the UIP) among the participants of existing clusters and offers them information on and contacts with the business and academic community as well as funding opportunities. In this sense, METI fundamentally changed its approach toward the cluster policy from the targeting and subsidization of particular industries to the facilitation of development and functioning of existing clusters, which is described as the "facilitation policy" (Hospers et al. 2009).

Third, METI's new policy approach is similar to the approaches of successful European clusters. Hospers et al. (2009) find out the following three elements that are common to the successful clusters in Europe[3]: (1) clusters utilize existing regional resources, (2) clusters steadily transform themselves according to their environment, and (3) public authorities are largely absent in the clustering process but organize networking events, offer technological advice, and provide business/financial matches that facilitate the function of clusters. Public support provided in the ICP is indeed comparable to that offered by the recent European clusters.

Finally, the geographical scope of each regional project is considerably wider than that of any other cluster policies, which implies that the ICP supports network formation both within and beyond local areas[4]. The definition of cluster boundaries is inherently vague. Most cluster policies focus on specialized narrow areas; however, as Desrocherz (2000) insists, local firms typically regard outside collaborative partners as more important than their neighbors even in highly advanced clusters such as Silicon

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[3] Hospers et al. (2009) select several regions such as Baden-Württemberg, Emilia-Romagna, Jutland, and Manchester as the examples of successful clusters in Europe.

[4] The ICP in the first period comprises 19 regional projects, most of which cover two or more prefectures (see Appendix 1).

Valley[5]. Thus, we expect to derive some important policy implications for the R&D performance of local firms by assessing the ICP.

3. Theoretical backgrounds and hypotheses

In this section, we explain the theoretical backgrounds of this paper. In particular, we are interested in the relationship between R&D productivity and regional clusters. Our discussion focuses on localized knowledge spillovers and is based on the approaches of the spatial economy (Fujita 2007), the nature of innovation process (Malmberg et al. 1996), and the concept of knowledge-specific failures (Arnold and Thuriaux 2003, Dobrinsky 2009). After discussing the theoretical backgrounds, we propose our main hypotheses.

3.1. Spatial economics approach

Fujita (2007) insists that the heterogeneity of people (workers), consumer goods, and intermediate goods is essential to the formation of agglomeration. Taking the diversity of human capital as an example, Figure 1 shows the circular causality in constructing the agglomeration of innovation activity and human capital.

[Insert Figure 1 here]

Starting with the bottom round square, high agglomeration of diverse people and supporting activities in a city leads to high productivity of innovation activity in this city through the interaction of heterogeneous skilled workers[6]. This, in turn, attracts more diverse people and supporting institutions. Then, the resulting increase in the innovation activities creates a demand for an even greater variety of people and supporting institutions in that city.

[5] Contrary to this discussion, Abramo et al. (2009) indicate the importance of information asymmetry in the market for UIPs. Their findings reveal that firms have the option of choosing more qualified research partners in universities located closer to the place of business.

[6] Though his argument is focused on the agglomeration in the cities, we expect it to be applicable to wider geographical areas.

This circular process is usually promoted by labor and related markets; however, the increase of localized knowledge spillovers through face-to-face communication among innovators in the area strengthens this virtuous circle and provides the city with a competitive advantage in innovation activity. The agglomeration of diverse skilled workers leads to the agglomeration of diverse knowledge and information. In particular, tacit knowledge is accumulated in the city through close interactions among skilled workers.

Previous literature also suggests the importance of localized knowledge spillovers. Jaffe et al. (1993) compare the geographical location of patent citations to that of cited patents in order to investigate the extent to which knowledge spillovers are geographically localized. They find that citations often come from the same federal state and Standard Metropolitan Statistical Area (SMSA), so that knowledge spillovers are localized. Zucker et al. (1994) examine the effects of university star scientists on the performance of Californian biotechnology firms. They insist that inherent in the discovery itself is the degree of natural excludability: if the techniques for replication are not widely known prior to the discovery, then any scientist wishing to build on the new knowledge must first acquire hands-on experience. In fact, they find that geographically localized effects occur for scientific discoveries characterized by natural excludability.

3.2. The nature of the innovation process

Malmberg et al. (1996) investigate why the accumulation of knowledge, essential to firms' competitiveness, involves important local elements, in spite of the recent trend of international economic integration. According to them, there are three elements of the local accumulation of knowledge.

The first element is related to the nature of the innovation process. The innovation process is fundamentally uncertain in terms of technological feasibility and market acceptance. Further, the ideas are frequently derived from outside the firm that actually conducts R&D and manufacturing. These characteristics of the innovation process imply that incremental and trial-and-error problem-solving enhances the need for continuous interaction, both formal and informal, with other organizations such as related companies, customers, universities, and public research institutes. Face-to-face contacts accelerate the accumulation and exchange of knowledge and thus smooth continuous interactions. In sum, the nature of the innovation process tends to locally confine the technological activity.

The second element is related to the extent of knowledge diffusion. If the knowledge diffuses rapidly and at a low cost, its agglomeration is not necessary. However, knowledge is differently mobile according to its characteristics. For example, knowledge embedded in human capital or social capital is much less mobile and bound to local circumstances. This type of knowledge, like tacit knowledge, is embedded in the local milieu and generates competitive advantage in the region.

The third element involves the attraction of outside resources. As the local milieu evolves, it will attract new people, firms, and supporting institutions. This argument is similar to Fujita's circular process.

3.3. Market failure, government failure, and knowledge-specific failures

There are two kinds of market failure concerning R&D. First, the gap between private and public returns to R&D caused by knowledge spillovers leads to incomplete appropriability of the R&D outcomes, which gives rise to market failure (Griliches, 1992; Spence, 1984; Teece, 1986). Second, R&D has three types of uncertainty: technological uncertainty, commercial uncertainty, and the behavioral uncertainty of rival firms (Malmberg et al. 1996). Under serious uncertainties, the level of private R&D investment would be suboptimal.

Industrial cluster can help overcome the two kinds of market failure on R&D. As mentioned above, firms in clusters can more easily build collaborative networks. It is shown that, when spillover is high, collaborative R&D with rival firms internalizes knowledge spillovers and enhances the incentive to invest in R&D (Suzumura 1992). Further, collaborative R&D reduces the three kinds of uncertainty through improved coordination and the pooling of risk and resources. Cluster policies promote the networking for collaborative R&D and hence contribute to overcoming market failure.

Moreover, the public sector can compensate for the underinvestment in R&D with R&D subsidies. Indeed, the ICP involves various R&D subsidies for cluster participants. Especially, government-sponsored R&D consortium provided by the ICP is not only an important R&D support for UIPs, but also a crucial channel to promote trust among the members (Das and Teng, 1998; Zucker et al., 2001; Darby et al., 2008), which would improve R&D efficiency through better coordination and information sharing. In this way, cluster policies will not only contribute to overcome market failure and increase R&D investment to the social optimum, but also increase R&D productivity of cluster participants.

Furthermore, government is considered to be endowed with capabilities to overcome various kinds of knowledge-specific failures in the knowledge-based economy (Dobrinsky 2009). Knowledge-specific failures involve a large number of agents or stakeholders and the complex links and interactions among them. Arnold and Thuriaux (2003) point out several aspects of such failures. For example, network failures are the problems in the interaction among different agents or stakeholders due to poor linkages and low degree of trust among them, and high transaction costs perceived. Capability failures of firms are their inability to act in their own best interests, which is derived from poor managerial or technological skills and the inability to absorb externally generated technologies.

These kinds of failures hinder the efficient development of UIP and decrease the R&D productivity of firms. Therefore, R&D support and networking/coordination support by the ICP is expected to be effective measures to cope with network failures and capability failures.

Government may also fail in achieving the optimal level of R&D and promoting innovation particularly due to information asymmetry between firms (or researchers) and government agencies (Wolf 1993). However, such government failure is considered to be less serious in the indirect support programs for network formation that is characteristic of the ICP than in the direct intervention policy. Moreover, support measures of the ICP are promoted and implemented by regional agencies in cooperation with the local non-governmental organizations such as trade associations and the chambers of commerce and industry. Potential government failure may also be mitigated in this way.

3.4. Hypotheses

As already mentioned, we are particularly interested in the effect of participation in the cluster project on patent applications as well as the role of collaboration with national universities. Our main hypotheses are presented as follows.

H1: The SMEs with UIP that participate in the cluster project apply for more patents than those that do not.

H2: Among the cluster participants, those collaborating with national universities in the same cluster area apply for more patents than those collaborating with other types of universities and public research institutes.

The first hypothesis compares the R&D productivity of SMEs with UIP in terms of patent application between the cluster participants and the others, while the second hypothesis compares it among the cluster participants with different types of research partners.

The first hypothesis relies on the above arguments. According to Fujita (2007) and Malmberg et al. (1996), local (e.g., face-to-face) communication among different people is important for accelerating regional innovation activities. Participation in the cluster project increases knowledge flow, promotes the accumulation of tacit knowledge, and decreases the uncertainty of innovative activity, through better access to local communication and collaboration with other partners. Moreover, knowledge-specific failures including network and capabilities failures can be mitigated by the support measures of the ICP. Thus, the participants of the cluster projects are more likely to achieve and increase innovative outputs.

Our sample consists of local SMEs engaged in UIP. Thus, this argument specifically means that cluster participants can find better (or more appropriate) partners than the others, or they can strengthen and improve their existing UIP, through the support programs provided by the ICP. We consider that, among various programs, matching events and seminars (networking support) are mainly related to the former story, while the latter effects are rather based on R&D support, technological consultation, and incubation services.

The second hypothesis is derived directly from the main purpose of the ICP. This project mainly aims at building collaborative networks among local SMEs and core national universities within each cluster region. SMEs have limited business resources, and the UIP provides them with the opportunity to mitigate this problem. The

ICP is expected to support local SMEs in finding optimal partners within the cluster. Specifically, METI recommends them to collaborate with national universities within the same regional cluster and gives them the incentive to do so through support programs such as the *Consortium R&D Project for Regional Revitalization*[7].

Furthermore, Japanese national universities have recently been required from the government to contribute to activating the local economy and to be actively engaged in the national policy, and thus to play the central role in the ICP. Such environmental change of the UIP is also the background of our second hypothesis.

4. Data and sample characteristics

In this section, we first explain our dataset and its sources. Our data are composed of three data sources: original questionnaire data, lists of cluster participants, and patent data. Then, we summarize the basic statistics of participants and non-participants in cluster projects in order to illustrate the differences between them.

4.1. Questionnaire data and the list of cluster participants

Our research is based on the data from an original survey conducted in 2005. Approximately 10,000 firms in the manufacturing sector with 20 or more employees were selected by random sampling from the JADE database of Bureau van Dijk. We obtained effective responses from 1,861 firms (19%), among which 520 firms were R&D-intensive SMEs with up to 300 employees[8]. We focus on such firms because the ICP aims to support local SMEs especially by promoting UIP between innovative firms and universities.

Among them, 75 firms (14%) participated in the ICP. 76% of the participants and 38% of the non-participants of the ICP engaged in UIP (this difference is significant at the one percent level). From among these firms, we finally selected 229 firms that

[7] This program provides financial support only to the R&D consortia that include national university in the region. Thus, it aims to promote local UIP with national universities. There were approximately 1,130 R&D consortia by 2004 and approximately 60% of them involved the participants of the ICP.

[8] Here, we define R&D-intensive firms as those that agreed to the following statement in our survey: "We appropriate R&D budgets every year." The definition of SMEs follows that of the SME Basic Law.

had engaged in research collaboration with universities or public research institutes during the preceding three years (2002-2004)[9].

As already indicated, knowledge spillovers are important for clusters as a useful source of innovations. However, it is difficult to measure knowledge flow quantitatively. We have an advantage in this regard. Our survey consists of two parts: (1) questions on firm characteristics and (2) those on the characteristics of UIP. Information on firm characteristics includes the year of establishment, the number of employees, location, industry classification[10], and the R&D ratio to sales. The characteristics of UIP include the type and location of partners, motivation, and the patterns of UIP.

In order to assess the effect of participation in regional clusters, we have to identify the participants of the cluster projects. Each organization supporting cluster formation provides a database of participating firms, universities, and public research institutes. We checked these databases and matched them with our survey data, considering company names and addresses. Finally, we found 57 participating firms among 229 R&D-intensive SMEs.

4.2. Patent data

We use the number of patent applications as a proxy for R&D outputs. Needless to say, patent data have several important limitations. First, the range of patentable inventions constitutes merely a sub-set of all research outcomes: for a patent to be registered, it must indeed be “novel,” “non-trivial,” and have potential “commercial application”, according to the Japanese patent law. Second, firms may deliberately choose not to apply for a patent but to keep it secret. Hence, not all patentable inventions are actually patented because of this trade-off between patenting and secrecy. However, patents are generally regarded as an appropriate index of invention counts in the empirical literature (Acs et al. 2002; George et al. 2002; Kim et al. 2005; Motohashi 2005; Jaffe and Trajtenberg 2002).

We collected patent applications from 2003 to 2005 by 229 sample firms through the Intellectual Property Digital Library (IPDL). Our survey was carried out in

[9] We focus on the firms with UIP in order to measure knowledge flow using the characteristics of UIP, as mentioned in the introduction.

[10] The industry classification in our survey roughly corresponds to the JSIC 2-digit level.

early 2005, in which we asked about the UIP during the preceding three years, from 2002 to 2004. Thus, we assume that patent applications between 2003 and 2005 are appropriate as invention outputs in our study. The estimation results do not considerably differ depending on whether we use as dependent variables the number of patent applications in each year or the total numbers in these three years. Therefore, to save space, we only provide the estimation results using the total number of patent applications between 2003 and 2005 as the dependent variable[11].

It is noteworthy that, by collecting patent application data in these three years, we may measure the early outcomes of the UIP projects from basic research, given that these projects were enabled by cluster participation after 2001. In the empirical analysis, we will control for the characteristics of the R&D projects using the dummy variables for the purposes of UIP.

Many researchers point out that the value of each patent is substantially different (Jaffe and Trajtenberg 2002). Thus, we also use the average number of claims and forward citations per patent as invention counts. These data are derived from the IPDL and Derwent Innovation Index of Thomson Reuters. Using these variables, Section 6.2 discusses the estimation results on the quality of applied patents.

4.3. Differences between participants and non-participants

Before considering the estimation strategies, we will first compare some firm characteristics between 57 participants (treatment group) and 172 non-participants (control group) of the cluster project in order to examine the endogeneity and the factors of cluster participation.

Table 2 summarizes the differences between the participants and non-participants in cluster projects. We conducted significance tests on the mean values and variances between them. Among the firm characteristics, only firm age is significantly different between them. There are no significant differences with regard to firm size and R&D intensity. However, the characteristics and the outcomes of UIP are different between these groups except for the partner types and the purposes of UIP[12]:

[11] The estimation results using patent data of each year are available upon request from the authors.
[12] Partner types are classified into the following categories according to the affiliation of the research partner: national university, other public university, private university, and public research institute. See

The cluster participants are significantly more likely to collaborate in the same cluster region. They tend to conduct joint R&D rather than the other patterns of UIP. Moreover, they often find their partners via the support offered by public agencies and UIP support centers of universities, while the non-participants rely to a larger extent on managers' personal networks in the partner search.

[Insert Table 2 here]

In the empirical models in Sections 5 and 6, we explicitly take into account the endogeneity of the participation in the cluster projects. The result that the basic firm characteristics of the cluster participants are not significantly different from those of the non-participants suggests that the former are not necessarily superior to the latter. However, the characteristics and the outcomes of UIP are partly different between them. This also implies that there is no serious problem in comparing these groups.

Moreover, as mentioned in Section 4.1, among the R&D-intensive SMEs, cluster participants are significantly more likely to engage in UIP than the others. Thus, cluster participation is positively correlated with the engagement in UIP. However, such bias of cluster participants toward UIP is controlled for in our analysis, because it focuses on the firms with UIP.

5. Analytical models

5.1. Basic models and variables

We conducted econometric analyses by using the unique dataset described in the previous section. The dependent variable, the number of patent applications, is count data (*pat*); therefore, we employ negative binomial estimation. In addition, we conduct Poisson, Tobit, and zero-inflated negative binomial regressions to check the robustness[13]. The basic patent production function is formulated as follows:

Table 3 and the following section with regard to the purposes of UIP.

[13] The results of these alternative estimations demonstrate no considerable differences from those of negative binomial regression. Therefore, we only provide the estimation results of the latter.

$$E[patent] = \lambda_i = \exp[\beta X_i]$$

The analytical unit *i* is the firm. Independent variables *X* include the dummy for participation in cluster projects, firm size, R&D intensity, the number of UIP projects, the dummies for the collaboration with national universities, joint R&D, the collaboration within the same cluster regions, and the purposes of UIP, as well as industry dummies. We also incorporate the interaction terms of cluster participation and other variables.

We identify 57 cluster participants and incorporate the dummy variable of the participation in a cluster (*participant*)[14], which takes on the value one if the firm participates in a regional cluster project and zero otherwise. Hypothesis 1 expects that the coefficient of this variable will be positive and significant. We further include the number of employees (*scale*) and the ratio of R&D expenses to sales (*rd*). R&D-intensive firms are expected to produce relatively more invention outcomes. Even after controlling for R&D intensity, larger firms tend to apply for more patents because they have more complimentary assets that may increase the innovative output and because they are usually more familiar with the procedures of patent application[15]. Therefore, we expect the coefficients of these variables to be positive and significant.

As for the UIP characteristics, we use the number of UIP projects during the preceding three years (*projects*), the dummy variable for collaboration with national universities (*national*), the dummy variable for joint R&D (*jointrd*)[16], the dummy variable for the collaboration within the same cluster region (*sameregion*), and the dummy variables for the purposes of UIP.

The dummy variable *jointrd* takes on the value one if the firm conducts joint R&D in UIP, and zero otherwise. Firms with joint R&D are supposed to be more active in applying for patents than those with the other types of UIP because joint R&D is the

[14] The effect of the participation in the ICP may take a long time to come out. Unfortunately, we cannot identify since when the firms have participated in the ICP. However, according to unofficial information from the METI, a majority of the participants, at least in the bio-clusters, were involved in the ICP from the very beginning of the project, i. e. since 2001.

[15] It is noteworthy that our sample comprises SMEs up to 300 employees. Thus, with this variable, we check and control for the size effect among SMEs.

[16] The UIP includes various patterns, such as joint R&D, commissioned R&D, technological consultation, technological licensing, and education/training. The baseline reference of joint R&D comprises any other patterns of the UIP.

most important and intensive collaboration among various patterns of UIP. The dummy variable *sameregion* takes on the value one if the firm cooperates with a partner in the same or neighboring prefectures, and zero otherwise [17]. If localized knowledge spillovers are important for the UIP as discussed before, this variable should have a positive impact on patent applications.

We should control for the difference in the types (e.g., basic research) and phases (e.g., early phase) of R&D projects in the UIP, because these differences may have significant impact on patent applications[18]. Unfortunately, however, such data are not available from our survey. Thus, instead, we include four dummy variables for the purposes of UIP (*d_purpose*) in order to control for the effects of different purposes, assuming that the purpose of UIP is related to the types and phases of the R&D projects. We consider here the following purposes of UIP: 1) to absorb the up-to-date scientific knowledge, 2) to commercialize business needs of the firm, 3) to bring technological seeds of the university into practice, and 4) to spare cost and time for R&D, regarding "the solution of concrete technological problems your company was faced with" as the baseline reference.

We also include the interaction term of *participant* and *log (scale)* in order to check if the effect of the participation in the ICP differs even among the SMEs according to the firm size. If the ICP effectively supports smaller firms, as METI intends to, then the coefficient of this term should be negative and significant.

We include further the triple interaction term of *participant* with *national* and *sameregion*. According to our second hypothesis, the coefficient of this term is expected to be positive and significant, that is, the cluster participants apply for more patents when they collaborate with national universities in the same cluster region, compared to the other cases.

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[17] The geographical area of a regional cluster is not clearly defined by METI, though, as mentioned before, the regional clusters usually cover two or more prefectures. Neither do we have a priori information on the optimal scope of an industrial cluster. Thus, in order to check whether or not we set appropriate criteria for the scope of an industrial cluster, we alternatively limit the cluster area to the same prefecture with the exceptions of Tokyo and Osaka, where they can easily collaborate with partners beyond the borders of the prefectures. Even by using this alternative definition of the cluster area, however, we obtained similar results.

[18] We are very grateful to an anonymous referee for suggesting this point.

Table 3 summarizes the basic statistics of variables. Appendix 2 shows the correlation matrix of these variables.

[Insert Table 3 here]

5.2. Endogeneity problem

There may be a serious endogeneity problem with regard to the variable *participant*. Namely, the firms that are more active in R&D and thus apply for more patents may be more likely to participate in the ICP. Further, METI might induce such innovative firms to participate in the cluster projects. In order to cope with this endogeneity problem and check the robustness of the estimation results of the basic model, we additionally estimate the instrumental variable (IV) and treatment effect (TE) models.

First, we conduct 2SLS (IV) estimation following Wooldridge (2002). This can be done by obtaining the predicted values of *participant*, regressing against the IV that is correlated with *participant* but exogenous to the dependent variable. We use firm age (*age*) as the IV, because the cluster project is aimed at attracting especially start-ups and young firms[19].

$$participant_i = \sum \theta_k Instruments_i + \varepsilon_i$$

Then, we estimate the basic model using the predicted values of *participant*.

Second, the TE model considers the effect of an endogenously chosen binary treatment on another endogenous variable. The regression function is described as follows:

$$patent_i = X_i \beta + \delta participant_i + u_i,$$

where *participant* is the endogenous dummy variable indicating whether or not the treatment is assigned. The binary decision is modeled as the outcome of an unobserved

[19] As mentioned in Section 4.3, average firm age is significantly different between the participants and non-participants of the cluster project at the 5% level (i.e., cluster participants are, on average, younger than non-participants). Moreover, the result of the first-stage estimation of the IV regression demonstrates that the coefficient of firm age is significant at the 1% level (see Table 5).

latent variable. It is assumed that the latent variable is a linear function of the exogenous variable *age* and a random component *v*.

$$participant_i^* = \varphi age_i + v_i$$

The observed decision is

$$participant = \begin{cases} 1, & \text{if } participant^* > 0 \\ 0, & \text{otherwise} \end{cases}$$

where *u* and *v* are bivariate normal with mean zero and covariance matrix

$$\begin{bmatrix} \sigma & \rho \\ \rho & 1 \end{bmatrix}.$$

6. Estimation results and discussions

6.1. Estimation results of the basic models and of those considering endogeneity

Table 4 shows the results of negative binomial regression of the basic model. The dependent variable is the total number of patent applications between 2003 and 2005. Model (1) includes independent variables *participant*, *log* (*scale*), *projects*, *national*, *jointrd*, *sameregion*, the dummy variables for UIP purposes (*d_purpose*), and industry dummies (*d_industry*). In Model (2), we incorporate the interaction term *participant* × *log* (*scale*). Model (3) includes the interaction term *participant* × *national* × *sameregion* in order to test the second hypothesis[20]. Our main concern is the coefficients of *participant*, *sameregion*, and these interaction terms.

[Insert Table 4 here]

[20] We also incorporated the interaction terms *participant* × *sameregion*, *participant* × *national*, and *participant* × *jointrd* in order to check the effect of cluster participation. However, the coefficients of these variables are not significant.

The coefficient of *participant* is not significant in all models. This means that the firms with UIP do not improve their R&D productivity by solely participating in the cluster projects. Thus, the first hypothesis is rejected[21].

Moreover, the variable *sameregion* shows a negative impact in all models. This result contradicts our expectations. If localized knowledge spillovers are important for UIP, this variable should positively affect R&D productivity, as discussed earlier. However, our results suggest that, on the contrary, the collaboration with partners in a distant area increases patent productivity. This implies that the firms should look for optimal partners according to specific research topics even when they are located in distant areas[22].

Contrary to this result, all of the coefficients of the interaction terms demonstrate positive effects on patent applications. The coefficient of the interaction term *participant* × *log* (*scale*) is positive and significant at the 10% level. This means that relatively large firms among SMEs benefit more from the participation in the ICP in terms of R&D productivity. It may also be easier for the relatively large firms to obtain more and better information on external resources in the ICP because they tend to be the core participants in the projects. This point may by crucial because, as discussed later, not every participant of the ICP exploit its various support programs: larger firms are more likely to utilize support measures of the cluster policy because they are better informed on these measures and they have more absorptive capacity of external resources.

The coefficient of the interaction term *participant* × *national* × *sameregion* is also significantly positive. This implies that participants in cluster projects apply for

[21] However, the results differ according to the technological focus of the regional clusters, such as biotechnology or IT. We will focus on this difference in another paper.

[22] Some may insist that the effect of participation in the cluster projects may be canceled out when the non-participants receive knowledge spillovers from the cluster participants. However, we argue that such knowledge spillovers, which may occur through patent information, formal collaboration as well as various informal contacts between the participants and non-participants, are not substantial for the following reasons. First, we use the number of patent applications between 2003 and 2005 as the invention counts by the UIP between 2002 and 2004. Considering the time lag of 18 months between the application and the publication of patents, it seems difficult for the non-participants to absorb and utilize knowledge from the patent applications by the participants. Second, according to our survey data, only 30% of the participants collaborate with other firms within the same clusters. Moreover, we find from additional estimations that, unlike the UIP, the collaboration with other firms does not have a positive impact on the R&D productivity of our sample firms. Therefore, although we do not know about informal contacts between the cluster participants and non-participants, we consider it to be rather unlikely that the effects of the participation in the ICP are completely canceled out by knowledge spillovers between them.

more patents only when they collaborate with national universities in the same cluster region. Thus, the second hypothesis is supported. In this sense, we can positively evaluate the ICP because it has the primary objective of promoting UIP in the *same* cluster area, especially with core *national universities*. We can derive an important implication from these results: In order to improve R&D productivity, firms should not only participate in the ICP but also collaborate with core national universities in the same cluster region.

Thus, the second hypothesis is supported, but not the first hypothesis. There can be several interpretations for this difference. First, participation in the ICP is no more than the registration via website, and not every participant of the ICP utilizes its support measures. Indeed, Nishimura and Okamuro (2009) show that, according to their recent survey, one-third of the cluster participants have not yet utilized any support programs. Without exploiting support programs, participants cannot improve R&D productivity even though they participate in the ICP. However, when the participants collaborate with national universities in the same cluster region, they are more likely to have used support programs because the ICP specifically aims at promoting such UIP. Moreover, because of this major aim of the ICP, cluster participants collaborating with national universities in the same region may have achieved better matching with the research partner than those collaborating with other types of partners.

Taken together with the variable *sameregion*, the result on this interaction term suggest that the negative effect of UIP in the local area (marginal effect of *sameregion*: –4.02) is more than compensated when the firm collaborates with a national university based on the ICP (marginal effect of the interaction term: 6.13).

The coefficients of the variables *log (scale)* and *rd* are positive and significant as expected. Apparently, larger firms and more R&D-intensive firms tend to apply for more patents. The variable *projects* has positive and significant impact on patent applications. Thus, generally speaking, UIP increases R&D productivity in our sample firms. The coefficients of *national* and *jointrd* are not significant in any models.

Dummy variables for UIP purposes are also included in the models, but not shown in this table. We found that UIP purposes have no effects on R&D productivity in any models. We introduced then the interaction terms of *participant* and *d_purpose*, without obtaining any significant coefficients. Thus, UIP purposes have neither direct nor indirect effects on R&D productivity of the firms engaged in UIP. Moreover, it is noteworthy that the variable *participant* has no effect and the triple interaction term has positive and significant effect on R&D productivity even after controlling for the characteristics of R&D cooperation represented by UIP purposes.

The empirical results of 2SLS and TE models, which take the endogeneity into consideration, are not different from those of the basic model. Thus, we just summarize the results of those models in Table 5.

[Insert Table 5 here]

These results suggest that the endogeneity problem of cluster participation is not serious for our sample firms. It may be because our sample firms are limited to R&D-intensive firms engaged in UIP, so that the differences in R&D intensity and UIP engagement between the cluster participants and non-participants are not considerable, as already mentioned in Section 4.3.

The above results are obtained by using the total number of patent applications from 2003 to 2005 as the dependent variable. However, as mentioned in Section 4.2, the results do not differ much when we use the number of patent applications in each year separately as the dependent variable.

Moreover, it is noteworthy that we focus only on the early outcomes of UIP by measuring the number of applied patents during the latter half of the first period of the ICP. This suggests that we may measure basic patents from the early phase of the R&D projects. For such patent applications, the quality is at least as important as the quantity. Hence, in the next section, we will check the effects on the average quality of applied patents.

6.2. Estimation results on the quality of applied patents

The estimation results with regard to the interaction term *participant* × *national* × *sameregion* have two interpretations. The first is that the cluster participants collaborating with national universities within the same cluster improve their R&D productivity thanks to the support in the cluster projects. The other is that these participants are induced to apply for more patents in order to show off the performance of the cluster project under political pressure: We can reasonably assume that METI (or the core organization of each cluster project) induces them to apply for more patents as the output of various supports so that its cluster policy might be highly validated.

It is not easy to test which story is true. One of the solutions to the problem is to investigate the quality of applied patents, which is expected to decrease if the participants increase the number of patent applications by succumbing to political pressure without improving the R&D productivity.

We collected data on the number of claims and forward citations of applied patents as the proxies for patent quality. The claims in the patent specification delineate the property rights protected by the patent. The larger the number of claims, the broader and the greater is the expected profitability of an invention. Both Tong and Frame (1994) and Lanjouw and Schankerman (2004) support the argument that the number of claims can be used as an appropriate quality index. Forward citations measure the number of times a patent is cited by other patents in the following years. Thus, a large number of forward citations suggest that the patent is highly evaluated by others (Jaffe and Trajtenberg 2002). These are the reasons why we use them as the quality indices of patents and analyze the impact of collaboration with national universities within the same cluster on the quality of applied patents.

As the dependent variables for the patent quality, we use the average number of claims of the patents applied from 2003 to 2005 and the average number of forward citations of the patents applied in 2003 and 2004. We cannot use the average number of forward citations of the patents applied in 2005 because the period since the registration of these patents is too short to measure the number of forward citations.

Table 6 shows the estimation results using the average number of claims and forward citations per applied patent as the dependent variables and the same independent variables as those in Table 4. Dummy variables for industries and UIP purposes are also included in the estimation models, but their results are not shown in the table. We control for the effects of industries (or technological fields) and UIP purposes considering that the characteristics of R&D projects may affect not only the quantity, but also the quality of applied patents. We conduct Tobit regression considering several zero values in the dependent variables[23].

[Insert Table 6 here]

According to Table 6, the coefficients of the interaction term of *participant*, *national*, and *sameregion* are not significant. This means that the quality of applied patents does not significantly decrease, while the number of patent applications increases, when the participants of the cluster project collaborate with national universities in the same cluster. This result is at least not consistent with the "pressure story." Thus, we cannot reject the possibility that the cluster participants collaborating with national universities in the same region do improve their R&D productivity thanks to the support provided by cluster projects.

If we use the average number of forward citations of the patents applied in 2003 as the dependent variable, the coefficient of the interaction term is rather positive and significant at the 10% level. By using the data of 2004, we cannot obtain significant results, which may be attributed to the citation lag.

Among the other variables, *rd* show positive and significant effects on patent quality in both measures. On the contrary, *participant*, *national,* and *joitntrd* have no effects on patent quality in both measures. These results are similar to those in Table 4 with regard to the numbers of patent applications. Thus, participation in the ICP improves neither the quantity nor the quality of patents. We find the significantly negative effect of *sameregion* not only on the number of patent application, but also on the average number of citations, but not on the average number of claims. Firm size represented by *log (scale)* has positive effects on the number of citations, but not on the number of claims. The purposes of UIP (*u_purpose*) do not affect the quality of applied patents, which is not shown in the table.

Thus, the empirical results on the average number of forward citations are similar to those on the number of patent applications, except for the effects of the number of UIP project (*projects*) and the triple interaction term. We found different

[23] Some firms did not apply for patents. In this case, we replace the average number of claims and citations with zero values. Estimation results remain unchanged when we omit them.

results between both measures of patent quality with regard to *log (scale)*, *projects*, and *sameregion*.

7. Conclusion

In this paper, we evaluate the ICP started by METI in Japan in 2001 in terms of UIP based on original survey data on SMEs. Our concerns are the effect of participation in the cluster project on patent applications and the role of collaboration with local national universities, which bring out the implication for the conditions necessary for effective organization of cluster policies for improving R&D performance.

Different from the preceding projects, the ICP aims at promoting local network for innovation, including collaboration with core national universities within each cluster. In particular, SMEs have limited business resources and difficulties in finding appropriate research partners; thus, the ICP is expected to support local SMEs in selecting optimal partners within the cluster. However, our results generally suggest that local firms collaborating with partners *outside* the cluster show higher R&D productivity both in terms of quantity and quality. This implies that a support system is necessary through which local firms can find appropriate partners according to research topics, even if such partners are located outside the clusters.

We find that the participation in the cluster project alone has no significant effect on the R&D productivity of firms, even after taking endogeneity into consideration. However, the cluster participants that collaborate with national universities in the same cluster region significantly improve the R&D productivity, without reducing the quality of applied patents. Therefore, we cannot attribute the positive impact of such collaboration to the administrative pressures on the participants to apply for more patents.

Similar to the support systems of successful European clusters, the ICP underscores the support of networking and autonomous development of local firms. The ICP provides both indirect networking/coordination and direct R&D support programs. Both programs are expected to help overcome market failures on R&D and knowledge-specific failures. Our empirical results indeed imply the effectiveness of indirect and direct support systems that lead to better matching among cluster participants and enhancement of efficiency in UIP[24].

In order to improve the R&D efficiency of local firms, it is generally important to construct a wide-range collaborative network within and beyond the clusters, although most clusters focus on the network at the narrowly defined local level. Focusing on cluster participants, however, our estimation results suggest that they improve their R&D productivity through the support programs of the ICP by collaborating with national universities in the same clusters rather than by collaborating with other partners including distant universities. Therefore, policymakers should concentrate on networking or R&D supports to build and develop collaborative network between cluster participants and core national universities if the former are willing to cooperate with research partners in the same clusters.

Even though participation in the cluster project alone does not generally lead to higher R&D productivity, the participants may obtain valuable information on potential partners through the support of the cluster projects. Such information may provide them with new opportunities to build networks with potential partners. This can be regarded as another important output of the cluster projects. Unfortunately, it is difficult to examine if the cluster participants started UIP after (or before) participating in the cluster projects, because our data are cross-sectional. Thus, it is beyond the scope of this study; Future research should investigate in more detail the effect of the cluster project on network formation by the participants.

To close this paper, we will mention some limitations of our study to illustrate future research agenda. First, we do not know in which year the firms participated in the ICP. Moreover, there may be a long time lag until the effect of participation in the ICP comes into appearance. In this paper, we assume that most firms participated in 2001 at the beginning of the ICP and measure the number of patent applications from 2003 to 2005, thus we may possibly underestimate the effect of participation. In addition, to assess the output of R&D investment and the effect of ICP, it may be important to take the types (basic research, applied research, or development) and stages (early or late

[24] Using our dataset, we cannot identify which types of support programs are more effective for improving firm performance. Nishimura and Okamuro (2009) suggest that indirect support programs may be more effective for the enhancement of firm performance. Falck et al. (2009) also insist on the effectiveness of networking supports of the cluster policy in Germany.

stage) of R&D explicitly into consideration. However, we have no detailed information in this regard, and used the purposes of UIP and industry dummies as proxies for the R&D types and phases of UIP engaged by firms.

Despite these limitations, however, this paper contributes to the literature and to the policy as one of the first empirical evaluations of cluster policies and by considering the conditions for effective organization of these policies. We expect to develop our research to comparative evaluations of cluster policies in different countries with different characteristics.

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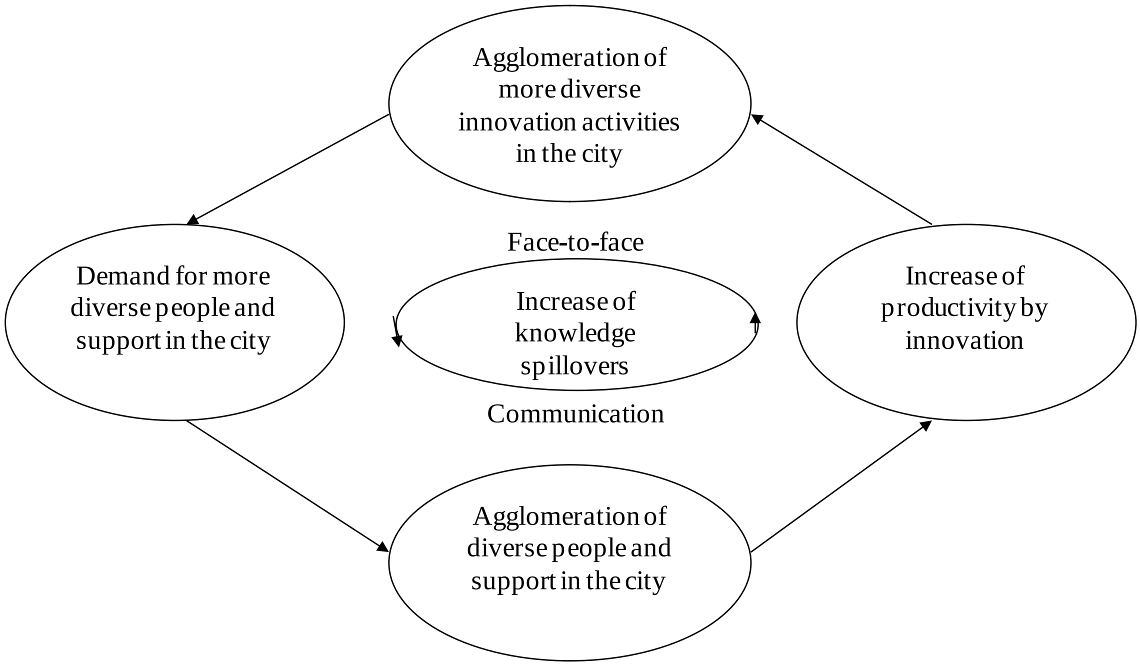
Tables and Figures

Figure 1

Building the innovation place through communication among diverse people



Source: Fujita (2007), p.9, Figure 5

Table 1

National cluster policies in Japan and Europe

Project Name	**Industrial Cluster Project**	**Cutting-edge cluster competition**	**BioRegio**	**Fond Unique Interministériel**	**Finnish Centre of Expertise (CoE) Program**	**Vinnväxt**
Country	Japan	Germany	Germany	France	Finland	Sweden
Budget	1.5 billion yen (2001－2005)	EUR 600 million	EUR 75 million	EUR 1500 million (2006－2008)	EUR 578 million (1999－2006)	75M SEK per year
Period	2001－2005 (first), 2005－2009 (second), 2010－2020 (third)	2007－2016/17	1995－2005	2006－	1994－1998 (first), 1999－2006 (second), 2007－2013 (third)	2003－2005 and at least 10 years onward
Program Initiator	Ministry of Economy, Trade and Industry (METI)	Federal Ministry of Research and Education (BMBF)	Federal Ministry of Research and Education (BMBF)	DGE (General Directorate for Enterprise, Ministry for Economy, Finance and Industry)	Ministry of Interior	Swedish Governmental Agency for Innovation Systems (VINNOVA)
Source of Fund	Ministry of Economy, Trade and Industry (METI)	Federal Ministry of Research and Education (BMBF)	Federal Ministry of Research and Education (BMBF)	Ministry for Economy, Finance and Industry, Ministry of Interior and regional development	Ministry of Interior, Ministry of Trade and Industry etc.	Swedish Governmental Agency for Innovation Systems (VINNOVA)
Number of Selected Regional Clusters	19	5	starting with 26, later focus on 3	71	13	12
Focus on SMEs	Yes	No	Yes	No	Yes	No
Cross Country/Interregional Activity	Yes (from the second period onward)	No	No	No	Yes (from the third period onward)	No
R&D Support	Collaborative R&D/networking	Collaborative R&D to support commercialisation	Application-oriented research	Applied research (The R&D projects must include at least two firms and a laboratory or a research centre.)	Collaborative R&D/networking	Very high, this is one of the main focuses of the program.
Selection Process and Program Contents	METI selects 19 regional projects based on comparative advantages and provides following supports: (1) network formation, (2) R&D support, (3) business start-up support, (4) marketing support, (5) management support, and (6) fostering human resources.	Based on applications or appointments: Regions/Cluster apply for and are selected through a competitive audition process. The program will single out Germany's top cutting-edge clusters in prioritized fields for awards and funding in a competition.	Based on applications or appointments: Regions apply for and are selected through a competitive audition process. Integrated concepts for biotechnology research and transfer of the results in industrial activity.	Based on applications or appointments: Regions/Clusters apply for and are selected through a competitive audition process. The aim is to support applied research for the development of services or products which could enter a market in a short/medium term.	The process is based on submission of proposals (more bottom-up type than top down). What the national level offers is long-term basic funding. The centres of expertise launch cooperation projects (public-private) between the research sector, educational institutions, and industry.	Based on applications: Regions should have established cooperation within the Triple Helix. The infrastructure of innovation systems should be built up, i.e., support for new companies, venture capital, and specialized work force, etc.

Source: METI (2005), European Cluster Observatory (http://www.clusterobservatory.eu/index.php?id=1&article=25&nid), Oxford Research (2008).

Table 2

Differences between 57 participants (treatment group) and 172 non-participants (control group) of the ICP

	Comparison of mean values	Comparison of variances
Firm age	Participants are younger (significant at the 5%)	No difference
Number of employees	No difference	No difference
Industry structure	–	No difference
R&D intensity	No difference	No difference
Partner type	No difference	No difference
Location of partners	Participants tend to collaborate with partners in the same or neighboring region (significant at the 5%).	No difference
Partner search	Participants depend on the support offerd by government agencies and UIP support centers, while non-participants depend on managers' personal network (significant at the 5%).	No difference
Patterns of UIP	Participants are more likely to conduct joint R&D (significant at the 5%).	No difference
Purposes of UIP	No difference	No difference

Source: Original survey data

Table 3

Definitions and basic statistics of variables

Variable	Definition	Obs.	Mean	Std. Dev.	Min	Max
pat	Number of patent applications by firm *i* between 2003 and 2005	229	8.56	13.41	0	100
claim	Average number of patent claims by firm *i* between 2003 and 2005	229	58.35	93.84	0	585
citation	Average number of forward citations by firm *i* between 2003 and 2004	229	0.90	2.89	0	34
participant	Dummy variable that takes on the value one if firm *i* participates in a cluster project	229	0.25	0.43	0	1
scale	Number of employees of firm *i*	229	142.08	83.33	20	300
rd	R&D ratio to sales of firm *i*	222	3.98	3.77	0.05	30
projects	Number of UIP projects from 2002 to 2004	210	2.06	1.39	1	10
national	Dummy variable that takes on the value one if firm *i* collaborates with national universities	220	0.52	0.50	0	1
jointrd	Dummy variable that takes on the value one if firm *i* conducts collaborative R&D	226	0.63	0.48	0	1
sameregion	Dummy variable that takes on the value one if firm *i* cooperates with a partner in the same or neighboring prefectures	225	0.72	0.45	0	1
age	Age of firm *i*	229	43.31	15.53	6	86

Table 4

Estimation results of negative binomial regressions

	Negative binomial regression		
	(1)	(2)	(3)
		pat	
Independent variables			
participant	0.182 (0.198)	−1.908 (1.256)	−0.182 (0.233)
log（scale）	1.645*** (0.258)	1.390*** (0.307)	1.629*** (0.253)
rd	0.079*** (0.024)	0.081*** (0.025)	0.078*** (0.024)
projects	0.168** (0.068)	0.199*** (0.076)	0.194*** (0.071)
national	0.146 (0.171)	0.129 (0.168)	−0.033 (0.179)
jointrd	0.214 (0.201)	0.158 (0.203)	0.139 (0.195)
sameregion	−0.464** (0.186)	−0.439** (0.184)	−0.622*** (0.205)
Interaction variables			
participant			
× *log（scale）*		0.986* (0.589)	
× *national* × *sameregion*			0.796** (0.375)
d_industry	included	included	included
d_purpose	included	included	included
constant	−3.738*** (0.677)	−3.184*** (0.747)	−3.530*** (0.669)
Sample size	197	197	197

Note 1: level of significance: *** 1%, ** 5%, * 10%.

Note 2: Robust standard errors in parentheses.

Table 5

Estimation results of 2SLS and treatment effect regressions (TER)

	2SLS regression		TER
	(1)	(2)	(3)
	First stage	Second stage	
	participant	*log (pat+1)*	*log (pat+1)*
participant		0.416 (0.973)	1.212 (1.390)
log (scale)	0.211** (0.105)	1.051*** (0.285)	1.144*** (0.250)
rd	−0.004 (0.008)	0.061*** (0.021)	0.058*** (0.020)
projects	0.063*** (0.023)	0.134* (0.080)	0.152*** (0.055)
national	0.048 (0.063)	0.109 (0.168)	0.121 (0.147)
jointrd	0.124* (0.072)	0.046 (0.223)	0.086 (0.169)
sameregion	0.071 (0.071)	−0.282 (0.186)	−0.262* (0.150)
age	−0.006*** (0.002)		
d_industry	included	included	included
d_purpose	included	included	included
constant	−0.410 (0.272)	−1.898** (0.821)	−2.432*** (0.806)
Number of samples	197	197	197

Note 1: level of significance: *** 1%, ** 5%, * 10%.

Note 2: Standard errors in parentheses.

Table 6

Estimation results on the quality of applied patents by Tobit regression

	Tobit regression			
	(1)	(2)	(3)	(4)
	claim		*citation*	
Independent variables				
participant	0.473 (0.714)	0.723 (0.922)	0.103 (0.162)	0.025 (0.212)
log（scale）	0.787 (1.001)	0.786 (1.001)	1.124*** (0.296)	1.132*** (0.298)
rd	0.306*** (0.083)	0.305*** (0.083)	0.038** (0.018)	0.039** (0.018)
projects	0.357* (0.215)	0.350* (0.202)	0.063 (0.052)	0.068 (0.054)
national	0.721 (0.615)	0.840 (0.675)	−0.013 (0.148)	−0.055 (0.166)
jointrd	0.557 (0.708)	0.586 (0.711)	0.205 (0.180)	0.194 (0.182)
sameregion	−0.781 (0.680)	−0.682 (0.718)	−0.550*** (0.162)	−0.588*** (0.177)
Interaction variables				
participant × *national* × *sameregion*		−0.590 (1.383)		0.177 (0.309)
d_industry	included	included	included	included
d_purpose	included	included	included	included
constant	−0.935 (2.655)	−1.072 (2.674)	−3.627*** (0.850)	−3.607*** (0.853)
Sample size	197	197	197	197

Note 1: level of significance: *** 1%, ** 5%, * 10%.

Note 2: Standard errors in parentheses.

Appendix 1

Overview of the regional clusters in the ICP in the first period (2001–2005)

Project No.	Project name	Tech fields	# of firms	# of universities	# of public research institutes	# of incubations	# of financial institutes	Budgets (million yens)	Cluster region (prefecture)
1	Hokkaido Super Cluster Promotion Project (IT)	IT	293	13	3	6	8	2026	Hokkaido
1	Hokkaido Super Cluster Promotion Project (Biotech)	Bio	92	16	5	8	42	4795	Hokkaido
2	Industry Promotion Project for Information Technology, Life Science and Cutting-edge Manufacturing	Manufacturing, IT, Bio	260	27	10	5	76	2734	Aomori, Iwate, Miyagi, Akita, Yamagata, Fukushima
3	Industry Promotion Project for a Recycling -oriented Society	Energy	340	25	11		76	1440	Aomori, Iwate, Miyagi, Akita, Yamagata, Fukushima
4	Regional Industry Revitalization Project (TAMA)	Manufacturing	300	37	5	7	17	2757	Tokyo, Kanagawa, Saitama
4	Regional Industry Revitalization Project (Chuo Expressway)	Manufacturing	240	7	5	3	12	2446	Nagano, Yamanashi
4	Regional Industry Revitalization Project (Tokatsu/Kawaguchi areas)	Manufacturing	350	16	4	5	7	2572	Chiba, Saitama
4	Regional Industry Revitalization Project (Sanennanshin district)	Manufacturing	550	5	2	4	2	1393	Shizuoka, Nagano
4	Regional Industry Revitalization Project (Northern Tokyo metropolitan area)	Manufacturing	210	6			2	3149	Tochigi, Gunma
5	Fostering of Bio-Ventures	Bio	240	19	6	9	8	3673	Ibaraki, Gunma, Saitama, Tokyo, Kanagawa, Chiba, Shizuoka
6	Fostering of IT-Ventures	IT	240	1			1	1668	Tokyo, Kanagawa
7	Project to Create Manufacturing Industry in Tokai Region	Manufacturing, IT	864	30	18	18	18	8237	Aichi, Gifu, Mie
8	Tokai Bio Factory Project	Bio	60	47	15	1	3	2241	Aichi, Gifu, Mie
9	Project to Create Manufacturing Industry in Hokuriku Region	Manufacturing	150	14	6	10	7	1273	Toyama, Ishikawa, Fukui
10	Bio Five-Star Company & Tissue Engineering Project	Bio	230	35	15	21	19	11063	Fukui, Shiga, Kyoto, Osaka, Hyogo, Nara, Wakayama
11	Active Manufacturing Industry support Project	Manufacturing	531	31	15		25	10654	Fukui, Shiga, Kyoto, Osaka, Hyogo, Nara, Wakayama
12	Kansai Information Technology Cluster Promotion Project	IT	480	15	3	14		937	Fukui, Shiga, Kyoto, Osaka, Hyogo, Nara, Wakayama
13	Kansai Energy & Environment Cluster Promotion Project	Energy	123	8	3		2	3259	Fukui, Shiga, Kyoto, Osaka, Hyogo, Nara, Wakayama
14	Project to Newly Generate the Machinery Industry in the Chugoku Region	Manufacturing	110	13	8	9	54	3206	Tottori, Shimane, Okayama, Hiroshima, Yamaguchi
15	Project to Form a Circulative Type of Indust	Energy	110	13	13		54	2656	Tottori, Shimane, Okayama, Hiroshima, Yamaguchi
16	Shikoku Techno Bridge Plan	Manufacturing, IT, Bio,	300	5	9		16	3040	Tokushima, Ehime, Kagawa, Kochi
17	Kyushu Recycle and Environmental Industry Plaza	Energy	184	19	6			1067	Fukuoka, Saga, Nagasaki, Kumamoto, Oita, Miyazaki, Kagoshima
18	Kyushu Silicon Cluster Project	Manufacturing, IT	150	33	8		5	4931	Fukuoka, Saga, Nagasaki, Kumamoto, Oita, Miyazaki, Kagoshima
19	Okinawa Industry Promotion Project	Manufacturing, IT, Bio,	170	4	2		6	1422	Okinawa

Source: Websites of each cluster project

Appendix 2

Correlation matrix of variables

	pat	*claim*	*citation*	*participant*	*scale*	*rd*	*projects*	*university*	*jointrd*	*cluster*	*age*
pat	1										
claim	0.31	1									
citation	0.09	0.37	1								
participant	0.17	0.12	0.04	1							
scale	0.26	−0.01	0.08	0.06	1						
rd	0.14	0.32	0.19	0.05	−0.13	1					
projects	0.15	0.18	0.01	0.22	−0.04	0.16	1				
university	0.10	0.12	0.04	0.09	0.04	0.08	0.11	1			
jointrd	0.12	0.17	0.10	0.22	−0.06	0.05	0.26	0.11	1		
cluster	−0.08	−0.12	−0.16	0.06	0.06	−0.10	−0.05	−0.14	−0.03	1	
age	0.07	−0.12	−0.14	−0.16	0.32	−0.18	0.00	0.02	−0.12	0.07	1