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

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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 a collaborative network 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. However, cluster participants apply for more patents than others without reducing patent quality when they collaborate with national universities in the same cluster region. These results imply the effectiveness of indirect support systems that remove obstacles and relax constraints in the clusters. In order to improve the R&D efficiency of local firms, it is also important to construct a wide-range collaborative network within and beyond the clusters, although most clusters focus on the network at a narrowly defined local level. These characteristics may be important factors for the effective organization of cluster policies.

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).

[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 firms participating in the ICP, and examine the effect of participation in the ICP and the UIP on patent productivity and the conditions necessary for the effective organization of cluster policies for improving R&D performance.

Cluster policies can be regarded as regional, industrial, or technological policies can be implemented as targeted subsidization or networking support under any of these aspects. Several scholars have recently been opposing the targeting and 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 about 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 1990). 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).

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[1]: (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[2]. The definition of cluster boundaries is inherently vague. Most cluster policies focus on specialized narrow areas; however, as

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

[2] The ICP comprises 19 regional projects, most of which cover two or more prefectures (See Appendix 1).

Desrocherz (2000) insists, local firms typically regard outside collaborative partners as more important than their neighbors even in highly advanced clusters such as Silicon Valley[3]. Thus, we expect to derive some important policy implications for the R&D performance of local firms by assessing the ICP.

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 and Lehmann 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 and skilled workers 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). Though it is difficult to measure knowledge flow quantitatively, we have an advantage in this regard, because our questionnaire data include information on the contents of UIPs, such as the types and locations of partners.

Our survey data as of 2005 comprise 229 R&D-intensive SMEs with up to 300 employees that had been engaged in university-industry collaboration during the preceding three years. 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 control group (non-participants).

We use the number of patent applications, claims, and forward citations from 2003 to 2005 as proxies for innovation counts by firms. Patent indicators are often used as proxies for R&D outcomes by UIPs (George et al. 2001; Kim et al. 2005; Motohashi 2005; Lööf and Broström 2008) and 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 endogeneity problem of participation in the cluster project.

[3] 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.

Our main results show that the number of UIPs increases R&D productivity, while 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 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 spatial economic theory and the nature of innovation process. In Section 4, we present our data construction and the basic statistics of the treatment and control groups. Section 5 discusses analytical models. Section 6 provides estimation results. We conclude our study in Section 7.

2. Overview of the ICP

METI started the ICP in 2001[4]; 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, for example, which is emphasized in METI (2005), METI established an organization that promotes cluster

[4] 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.

formation; dispatches coordinators to participating companies and universities; holds university-industry collaboration exchange, seminars, and symposia; 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).

Nineteen regional clusters were supported by METI between 2001 and 2005. Appendix 1 shows the characteristics of each cluster, for example, technological fields, 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 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 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 second project and it is simpler to assess the R&D outputs than total effects of clusters.

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) and the nature of innovation process (Malmberg et al. 1996). 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. 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.

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. (1992) 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 (p. 9). 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 technology 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. Hypotheses

As already mentioned, we are particularly interested in the effect of participation in the cluster project on patent applications, patent quality, and the role of collaboration with national universities (UIP). Our main hypotheses are summarized as follows.

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

H2: The effect of participation in the cluster project on R&D productivity is enhanced by collaboration with national universities within the cluster area.

The first hypothesis relies on the above argument. 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. Thus, the participants of the cluster project are more likely to achieve innovative outputs.

The second hypothesis is derived directly from the intention of the industrial cluster policy. This project mainly aims at building collaborative networks among SMEs and core national universities within each region. 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 cluster project is expected to support local SMEs in finding and selecting optimal partners within the cluster. Specifically, METI recommends them to collaborate with national universities within the cluster and gives them the incentive to do so through support programs such as the Consortium R&D Project for Regional Revitalization[5].

Furthermore, Japanese national universities are required to contribute to activating the local economy and be actively engaged in the national policy for administrative cost subsidy from the government. This implies the central role of national universities in the industrial cluster policy formulated by METI. Local interactions among diverse researchers may reinforce localized knowledge spillovers

[5] The Consortium R&D Project for Regional Revitalization is the main R&D support program for industrial clusters. This program aims to promote local collaboration between industry and university. There were approximately 1,130 R&D consortia by 2004 and approximately 60% of them involved the participants of the ICP.

through face-to-face communication. This is supported by the idea of the nature of innovation process overcoming the uncertainty of innovation.

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 identifying 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 597 firms had been engaged in research collaboration with universities or public research institutes during the preceding three years. From among these firms, we finally selected 229 R&D-intensive[6] SMEs with up to 300 employees.

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[7], and the R&D ratios 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,

6 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.”

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

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 innovations 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." Second, firms may deliberately choose not to apply for a patent but to keep it secret. Hence, not all patentable innovations are actually patented because of this trade-off between patenting and secrecy. However, patents are generally regarded as an appropriate index of innovation counts in the empirical literature (Acs et al. 2002; George et al. 2001; 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). The survey was carried out in early 2005, in which we asked about the UIP during the preceding three years. Thus, we assume that patent applications between 2003 and 2005 are appropriate as innovation outputs in our study. The estimation results do not considerably differ when we use the number of patent applications from 2003 to 2005 and those in these three years together as dependent variables. 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[8].

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 innovation counts[9]. These data are derived from IPDL and Derwent Innovation Index of Thomson Reuters. Section 6.2 discusses the quality-adjusted estimation results with these variables.

[8] The estimation results using patent data of other years are available upon request from the authors.
[9] Estimations employing the average number of claims in patent applications in different years as dependent variables yield similar results. However, we cannot estimate the factors of patent quality using the number of forward citations of the patents applied in 2005 because the period since then is too short to measure the number of forward citations.

4.3. Differences between participants and non-participants

Before considering the estimation strategies, we will first compare some firm characteristics between the 57 participants (treatment group) and 172 non-participants (control group) of the cluster project in order to examine the possibility of endogeneity and 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 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 outcomes of UIP are different. The cluster participants are significantly more likely to collaborate with partners in the same cluster region. They often find their partners via the support offered by administrative agencies and UIP support centers at universities, while the non-participants depend to a larger extent on managers' personal networks in the partner search. Non-participants are significantly more satisfied with the achievement of UIP.

[Insert Table 2 here]

In the empirical models in Sections 5 and 6, we explicitly take into account the endogeneity problem of participation in 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 outcomes of UIP are partly different between them. This also implies that there is no considerable problem in comparing these groups.

5. Analytical models

5.1. Basic model 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 regression, Tobit regression, and zero-inflated negative binomial regression to check the robustness[10]. The basic patent production function is formulated as follows.

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

Firm is the analytical unit *i*. Independent variables *X* include participation in cluster projects, firm size, R&D intensity, the number of UIP projects, collaboration with national universities, joint R&D, collaboration within the same cluster regions, and 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 participation in a cluster (*participant*), which takes on the value one if the firm participates in a 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 innovation 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. 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 (*university*), the dummy variable for joint R&D (*jointrd*)[11], and the dummy variable for collaboration within the same cluster region (*cluster*). The dummy variables *university* and *jointrd* take on the value one if the firm collaborates with national universities and if the firm conducts joint R&D, respectively. Firms with UIP, especially with joint R&D, are supposed to be more active in applying for patents. The dummy variable *cluster* takes on the value one if the firm cooperates with a partner in

[10] 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.

[11] The UIP includes various patterns, such as joint R&D, commissioned R&D, technological consultation, technological licensing, and education/training. Among these patterns, joint R&D can be regarded as the most important and intensive collaboration. The baseline reference of this dummy variable comprises any other patterns of the UIP.

the same or neighboring prefectures[12]. If localized knowledge spillovers are important for the UIP as discussed before, this variable should have a positive impact on patent applications.

We also include the interaction terms of *participant* with *cluster*, *university*, and *jointrd*. The coefficients of these interaction terms are expected to be positive and significant because the cluster participants have a competitive advantage thanks to the support provided by METI and local communications in the cluster. Our second hypothesis expects that the interaction term of *participant*, *university*, and *cluster* has a positive effect on patent applications. 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*. Cluster participants may be more actively engaged in R&D and UIP and thus be more willing and likely to apply for patents. Further, METI might induce such innovative firms to participate in cluster projects. In order to cope with this endogeneity problem and check the robustness 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[13].

[12] The geographical area of a regional cluster is not clearly defined by METI. We also do not have a priori information on the optimal scope of an industrial cluster. Thus, in order to check whether we set appropriate criteria for the scope of an industrial cluster, we alternatively limit the cluster area to the same prefecture. However, we apply another wider scope of cluster to the firms in the metropolitan areas around Tokyo and Osaka, where they easily transact and collaborate with partners and people beyond the borders of the prefectures. The estimation results do not differ according to the definition of the cluster.

[13] 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 IV regression demonstrates that the coefficient of firm age is significant at the 1% level (see Table 5).

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

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 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

6.1. Estimation results of 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*, *university*, *jointrd*, *cluster*, and industry dummies (*d_industry*). In Model (2), we incorporate the cross-term *participant* × *log* (*scale*). Model (3) includes the cross-term *participant* × *university* × *cluster* in order to test the second hypothesis[14]. Our main concern is the coefficients of *participant*, *cluster*, and these interaction terms.

[Insert Table 4 here]

The coefficient of *participant* is not significant in all models. This means that firms do not improve their R&D productivity by participating in cluster projects. Thus, the first hypothesis is rejected[15]. Moreover, the variable *cluster* 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 collaboration with partners in a distant area increases patent productivity. This implies that firms look for optimal partners according to specific research topics even when they are located in distant areas[16].

Contrary to this result, all of the coefficients of the interaction terms demonstrate positive effects on patent applications. The coefficient of the cross-term *participant* × *log* (*scale*) is positive and significant. This means that larger firms benefit more from participation in cluster projects in terms of R&D productivity. It may also be easier for

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[14] We also incorporated the cross-terms, *participant* × *cluster, participant* × *university,* and *participant* × *jointrd* in order to check the effect of cluster participation. However, the coefficients of these variables are not significant.

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

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

larger firms to obtain greater and better information on external resources because they tend to be core participants in the projects.

The coefficient of the cross-term *participant* × *university* × *cluster* is also significantly positive. This implies that participants in cluster projects apply for 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 cluster projects but also collaborate with core national universities in the same cluster region.

The coefficients of the variables *scale* and *rd* are positive and significant as expected. Apparently, large firms and R&D-intensive firms tend to apply for more patents. The variable *projects* has a positive impact on patent applications. Thus, generally speaking, UIP increases R&D productivity in our sample firms. The coefficients of *university* and *jointrd* are positive as expected but significant only in Model (1).

The empirical results of 2SLS and TE models, which take the problem of 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 cluster participants and non-participants are not considered, as already mentioned in Section 4.3.

6.2. Estimation results of quality-adjusted R&D productivity

The estimation results with regard to the interaction term *participant* × *university* × *cluster* 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 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 innovation. 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 suggests that the patent is highly evaluated by others (Jaffe and Trajtenberg 2002). These are the reasons why we use them as quality indexes of patents and analyze the impact of collaboration with national universities within the same cluster on the quality-adjusted R&D productivity.

Table 6 shows the estimation results in which we use the average number of claims and forward citations as the dependent variables and the same independent variables as those in Table 4. We conduct Tobit regression considering several zero values in the dependent variables[17].

[Insert Table 6 here]

According to Table 6, the coefficients of the interaction term of *participant*, *university*, and *cluster* are not significant. This means that the quality of applied patents

[17] Some firms did not apply for patents. In this case, we replace the average number of claims and citations with zero values. Estimation results are not different if we omit them.

does not significantly decrease[18], 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.

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 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 aimed 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 they are located outside the clusters.

We find that 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 patents applied for. Therefore, we cannot attribute the positive impact of such collaboration to the administrative pressures on the participants to apply for more patents.

[18] If we use the number of forward citations in 2003 as the dependent variable, the coefficient of the cross-term is rather positive and significant at the 10% level.

As mentioned before, the ICP has characteristics similar to the support systems of successful European clusters, such as the support of networking and autonomous development. Our estimation results imply the effectiveness of such indirect support systems that remove obstacles and relax constraints in the cluster (Hospers et al. 2009; Porter 2000). In order to improve the R&D efficiency of local firms, it is 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. These characteristics may be important factors for the effective organization of cluster policies.

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 start UIP after (or before) participating in the cluster projects, because our data are cross-sectional. Thus, it is beyond the scope of this study; we hope to investigate the effect of the cluster project on network formation by the participants in the future.

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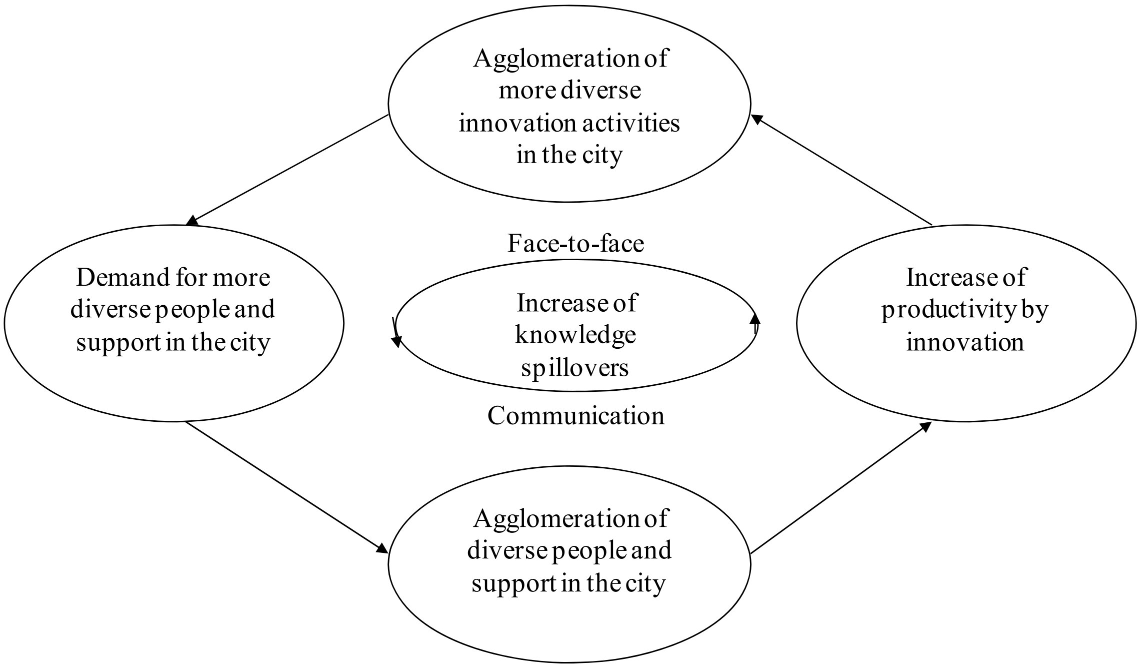
Tables and Figures

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
Type of UIP	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
Subjective evaluation of UIP	Non-participants perceive higher degree of achievements (significant at the 5%)	No difference
Patterns of UIP	Participants are more likely to conduct joint R&D (significant at the 5%).	No difference

Source: Original survey data

Table 3

Variable definition and basic statistics

Variable	Definition	Obs.	Mean	Std. Dev.	Min	Max
pat	Total number of patent applications by firm *i* between 2003 and 2005	229	8.56	13.41	0	100
claim	Average number of claims in patents applied by firm *i* between 2003 and 2005	229	5.02	3.67	0	17.5
citation	Average number of forward citations in patents applied by firm *i* between 2003 and 2004	229	0.09	0.36	0	4.9
participant	Dummy variable that takes on the value one if firm *i* participates in a regional 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 conducted between 2002 and 2004	210	2.06	1.39	1	10
university	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 in UIP	226	0.63	0.48	0	1
cluster	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 by negative binomial regressions

	Negative binomial regression		
	(1)	(2)	(3)
		pat	
Independent variables			
participant	0.160 (0.198)	−1.671 (1.280)	−0.126 (0.225)
log（scale）	1.643*** (0.251)	1.419*** (0.300)	1.641*** (0.246)
rd	0.076*** (0.023)	0.077*** (0.024)	0.078*** (0.024)
projects	0.176*** (0.066)	0.206*** (0.074)	0.191*** (0.068)
university	0.144 (0.170)	0.135 (0.168)	−0.001 (0.179)
jointrd	0.283* (0.179)	0.216 (0.181)	0.219 (0.177)
cluster	−0.428** (0.182)	−0.409** (0.181)	−0.544*** (0.195)
Interaction variables			
participant			
× *log（scale）*		0.864* (0.504)	
× *university* × *cluster*			0.635* (0.355)
d_industry	included	included	included
constant	−3.714*** (0.645)	−3.241*** (0.702)	−3.538*** (0.632)
Sample size	199	199	199

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

Note 2: Robust standard errors in parentheses.

Table 5

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

	2SLS regression		TER
	(1)	(2)	(3)
	First stage	Second stage	
	participant	*log (pat+1)*	*log (pat+1)*
participant		0.615 (0.984)	1.341 (1.415)
log（scale）	0.208** (0.104)	1.027*** (0.284)	1.153*** (0.245)
rd	−0.003 (0.008)	0.060*** (0.021)	0.056*** (0.020)
projects	0.061*** (0.023)	0.123* (0.071)	0.153*** (0.054)
university	0.057 (0.062)	0.093 (0.168)	0.116 (0.146)
jointrd	0.125* (0.068)	0.060 (0.220)	0.127 (0.163)
cluster	0.071 (0.069)	−0.268 (0.185)	−0.226 (0.165)
age	−0.006*** (0.002)		
d_industry	included	included	included
constant	−0.422 (0.260)	−1.792** (0.817)	−2.472*** (0.791)
Number of samples	199	199	199

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

Note 2: Standard errors in parentheses.

Table 6

Estimation results of the quality-adjusted R&D productivity by Tobit regression

	Tobit regression			
	(1)	(2)	(3)	(4)
	claim		*citation*	
Independent variables				
participant	0.498 (0.710)	0.765 (0.906)	0.106 (0.162)	0.023 (0.210)
log（scale）	0.776 (0.977)	0.770 (0.976)	1.058*** (0.282)	1.072*** (0.285)
rd	0.309*** (0.082)	0.308*** (0.082)	0.038** (0.018)	0.038** (0.018)
projects	0.334* (0.205)	0.330* (0.200)	0.044 (0.052)	0.050 (0.053)
university	0.685 (0.608)	0.813 (0.665)	−0.021 (0.147)	−0.066 (0.165)
jointrd	0.570 (0.673)	0.603 (0.676)	0.297* (0.174)	0.289* (0.170)
cluster	−0.767 (0.667)	−0.662 (0.702)	−0.513*** (0.159)	−0.555*** (0.174)
Interaction variables				
participant × *university* × *cluster*		−0.636 (0.703)		0.188 (0.303)
d_industry	included	included	included	included
constant	−0.889 (2.563)	−1.032 (2.580)	−3.363*** (0.802)	−3.351*** (0.805)
Sample size	199	199	199	199

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

Note 2: Standard errors in parentheses.

Appendix 1

Overview of 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