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The Case Study of Robot Technology in Japan

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Investigating Collaborative R&D Using Patent Data:
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Abstract: The growing trend of collaborative R&D has been well documented recently, both at a global level and through national and industry case studies. However, there is not yet any consensus regarding the following decisive questions: what are the exact level and evolution of R&D collaboration? What are the benefits of collaboration? What are the motives and determinants of firms engaging in R&D collaboration? In our opinion, these questions have not yet been answered due to the limitations of the data used in most empirical studies (large questionnaire surveys or very specific case studies).

The main novelty of this paper is the use of patent data with a focus on information concerning inventors. These data are less biased than questionnaire surveys in terms of the size of the institutions; they are objective and are particularly appropriate for analyzing the benefits of collaboration. As the identification of the institutions to which individual inventors are affiliated is a particularly time consuming task, we focus on robot technology in Japan since the beginning of the 1990s.

Our results are as follows. First, although the level of R&D collaboration in RT in Japan increased between 1991 and 2004, especially in the case of collaboration between firms and universities, it still remains low and is dominated by inter-firm collaborations. Second, we cannot definitively reject the conclusion that only the scale of the research has an impact on the quality of patents, when the unit of analysis is the patent; however, we show that there are significant spillover effects of collaboration, which imply an indirect effect on quality. Third, the determinants and motives which encourage firms to decide to engage in collaborative research differ depending on the partner they are collaborating with. In the case of collaboration with other firms, IO theories hold, as the existence of spillovers acts as an incentive. Regarding the collaboration with universities and public research institutes, the validity of capability theory, which emphasizes the quest for complementary knowledge and capability, is confirmed by our empirical investigation.

JEL Classification: O31, O32, O34

Key words: collaborative R&D, robot technology, patent data.

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Introduction

There has been a remarkable increase in the empirical literature on R&D collaboration during the last ten years. The increasing interest in this topic was partly caused by the increase in the number of collaborative R&D and its importance in firms' innovative activities. The major questions asked in past quantitative analysis can be classified into the following three issues:

-What are the trends in R&D collaboration?

-Can we find benefits from participating in R&D collaboration?

-What are the motives and determinants for firms to engage in R&D collaboration?

Although the empirical literature provides us with valuable insights, it presents heterogeneous results and has not brought about any consensus on these issues. This is partly due to the fact that systematic databases on R&D collaboration are rarely available. Most empirical studies use questionnaire survey data[2] or data from academic papers[3]. These methods inevitably encounter the problem of sampling biases. The drawback of the former research method is that the data are usually based on samples focusing on big institutions. The latter method is based on samples that are biased toward the R&D activities of scientists.

This paper contributes to the empirical literature on R&D collaboration by using patent data to investigate the three questions mentioned above. There are several advantages of using patent data. First, it contains data on smaller firms, so the sample is less biased than questionnaire surveys in terms of the size of institutions. Moreover, patent data contain information such as the number of claims, citations, inventors, and technological fields, which can be used as indicators of the quality of the R&D. These indicators are a more objective benchmark for measuring the benefits of collaboration than the opinions of managers, which are usually used in the analysis of questionnaire surveys[4].

In spite of these advantages, patent data have rarely been used to investigate collaborative R&D. One reason for this stems from the fact that patent data in many cases do not contain the name of the institution to which the inventors are affiliated. An alternative method to using the information of inventors is working with the patent applicant's data[5]. But it has been widely argued that data on applicants are not enough to investigate R&D collaboration, as only a part of collaborative R&D results in joint application[6].

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[2] Examples include Belderbos et al (2004), Hadgedoon and Van Kranenburg (2003), Hadgedoon (2002), and Hagedoorn et al (2000).

[3] Examples include Cockburn and Henderson (1998), Nakamura and Ueda (2006).

[4] Nevertheless, there are a couple of limitations in using patent data. According to Jaffe and Trajtenberg, (2002), the range of patentable innovations constitutes just a sub-set of all research outcomes, since in order for a patent to be registered, the research outcome should be "novel", "non-trivial" and with potential "commercial application". Second, not all patentable innovations are actually patented as firms may deliberately choose not to apply for a patent but to keep the innovation a secret.

[5] For example, Okada et al (2006) conducts detailed research on patents in the biotech industry in Japan, using the information of applicants to investigate the collaborative research in this industry.

[6] For example, Giuri and Mariani (2005) conducted a questionnaire survey and constructed a database of patent inventors which include 9 017 European patents. They found that 6.1% of all patents are co-applied patents,

In order to take full advantage of patent data, we obtained the information of the affiliated institutions of inventors. This enables us, for the first time in the literature, to analyze collaborative R&D based on the inventor information of patent data. To identify the affiliated institutions of inventors requires, however, an enormous amount of time and effort; therefore, we restricted our analysis to robotics technologies (RT) in Japan between 1991 and 2004. The RT provides a very interesting case study for collaborative R&D as a lot of institutions of various kinds have engaged in R&D activities. Also, the industry, in which Japan leads in production and research capabilities, has undergone dramatic technological development but has failed to enlarge the market. Many argue that a key for the development of this industry is to promote collaboration. The analysis of R&D collaboration in this sector should help to identify the factors for further development in this field.

The remainder of this paper is organized as follows. Section 1 provides a brief overview on the nature of robot technology in Japan and explains why we choose this industry as a case study. Section 2 describes the dataset. Section 3 summarizes the trend in collaboration in RT. Section 4 empirically analyzes the benefits of collaborative research. Finally, section 5 examines the motives and determinants for firms to engage in R&D collaboration.

1. Significance of robot technology in the study of collaborative R&D

Japan deserves to be called the robot kingdom, as it holds 45% of the world's robot stocks (2002) and is ranked first in the world in production. There have been a series of new movements in R&D and dramatic technological advances in robotics technologies since the early 1980s. Namely, many firms have invested a lot of effort inventing service robots, which can be used outside of factories like in households and public places. The development of R&D in new directions went hand in hand with the entry of many firms in various industries into the robot industry. At present, firms that engage in RT include industrial robot makers (such as Fanuc and Yasukawa), electric appliance makers (such as Sony, Fujitsu, NEC, Matsushita, Omron), automotive makers (such as Honda and Toyota), general machinery makers (such as Fuji Heavy Industries and Mitsubishi Heavy Industries), securities companies (such as SECOM and ALSOK), and venture firms that specialize in RT (such as Tmsuk and ZMP). Among these firms, Honda and Toyota are the most aggressive in terms of research and inventions in service robots, and ASIMO by Honda is one of the outcomes of their R&D activities. Other examples of inventions of service robots include humanoid robots by Fujitsu, a network robot by NEC, and AIBO by Sony.

The R&D in these new technologies in RT has actually attracted a great deal of public attention, and central and local governments support this industry in the form of the public projects and subsidies.

whereas 20.5% of all patents are the result of R&D collaboration with other partners. This implies that the analysis of collaboration based on applicant data would lead to the underestimation of R&D collaboration.

Also, public research institutions such as AIST (National Institute of Advanced Industrial Science and Technology) have conducted their own research in this field. It should be also noted that several university labs such as Waseda University, the University of Tokyo, and Tokyo Institute of Technologies have been pioneers in many fields of robot technology, and there are vast domains of knowledge in universities in RT. Robotics technology had been thought of having little linkage to science, yet increasing complexities in RT has increased the integration of science and technology in this field (Kumaresan & Miyazaki, 1999). Several firms looking to invent novel products are quite keen to cooperate with universities. Also, governments' effort to promote the collaboration between universities and firms in public projects is quite remarkable.

The R&D activities of these institutions, however, have not yet released new products that are successful on the market. There are several explanations for this, but many point to the lack of cooperation among firms as a major impediment for the R&D in RT to bring about fruitful results in business. For example, JARA (2001) states that "Robots are systems, and as such contain many different forms of highly specialized technology. No one company can possibly handle all aspects of robots systems. A faster and more efficient way to develop robots products is for several companies to work together and pool their resources". Thus, collaboration in R&D is a key issue for the development of the robot industry.

Although RT has undergone remarkable technological development and has attracted a lot of public attention, this industry has not attracted much attention in the economic literature, and the only recent academic paper that analyzes it is Kumaresan & Miyazaki (1999). While there are several other reasons that RT should draw the attention of more economic researchers, the significance of RT remains its relevance to the study of collaborative R&D. As a lot of institutions in different sectors have engaged in R&D, RT provides a very interesting case study for collaborative R&D. Analyzing the R&D collaboration should in turn help us to find grounds for developing this industry since facilitating beneficial collaboration is an important factor for the development of this industry.

2. Database and methodology

2.1 Data sources

The dataset used in our analysis is drawn from two complementary data sources: Industrial Property Digital Library (IPDL) and Standardized Data ("Seiri-Hyojyunka Data"). We merged the data from these two sources in order to obtain more comprehensive information in terms of the number of patents and their related information. For example, the Standardized data contains information on the citations of each patent, while the IPDL data do not. On the other hand, the IPDL data contain the technological fields of each patent, which are classified into 4 macro- and 26 micro-technological fields of RT (figure 1), while the standardized data do not include this information[7]. Furthermore, it is not possible to identify which patents are RT-related patents in the Standardized data, whereas this information is readily available in the IPDL data. Finally, the periods covered by each dataset are different: the Standardized data are from the 1960s to 2001, whereas the IPDL comprises data from 1991 to 2004, whose 1991 and 1992 data are incomplete.

=== Insert Figure 1 around here ===

Based on the definition by JPO (2002), we collected 16 736 RT-related patents between 1991 and 2004 through the IPDL data (comparing the application numbers of the two data sources, we matched 12 863 of these patents with patents from the Standardized Data). The data we collected contain basic information on each patent such as applicants, inventors, addresses, application (priority) years, technological classifications (20 micro-classifications). It also contains information related to patent quality, such as the number of claims and forward and backward citations.

2.2 Identification of inventors' affiliations

As noted earlier, our strategy is to identify collaborative research based on information concerning the inventors. We used the following procedure to achieve this. Among the 16 736 patent data in our dataset, there are 36 387 inventors. First, we checked these inventors one by one and identified 18 814 distinct individual inventors, who may have changed their affiliation over time. Out of these 36 387 inventors, we were then able to easily identify the affiliation of 31 572 inventors as the bibliography of patents already specifies which institutions they belong to. For the remaining 4 815 inventors, we used various search engines (including ReaD, the search engine by the Japan Science and Technology Agency, JST) to identify the institutions they belong to. In the end, we were able to identify the affiliated institutions of 33 733 inventors. We excluded 2 271 non-Japanese inventors because we are interested in patents applied for by Japanese inventors. There are also 393 unknown inventors. The 33 733 inventors we identified correspond to 15 463 patents between 1991 and 2004.

2.3 Classification of patents

After having identified the institutions to which the inventors belong, we classified them into three types: firm, university, and public research institute. We found that 32 035 inventors belong to firms, 923 to universities, and 775 to public research institutes. We then classified each patent into 10 sub-groups, based on the type of institution the inventors belong to. When there were more than two

[7] Yet, for some reason, JPO does not disclose the classification information on six micro-categories ("other robot", "modular structure", "attachment", "control unit to operate with a foot", "virtual reality", "and networking technology"), which made us limit our analysis to 20 micro-technological fields. We did not receive a satisfying answer from JPO why they are not available. This is probably due to identification problems for theses six technologies.

related institutions, our classification is based on the combination of these types (table 1). There are 10 possible cases, which include three cases of non-collaborative inventions: one firm only, one university only, one public research institution only. Three cases are collaboration with partners of the same type: collaboration between firms, collaboration between universities, and collaboration between public research institutions. The other four cases are collaboration with partners of different type(s): firm(s) and university(ies); firm(s) and public research institution(s); university(ies) and public research institution(s); firm(s), public research institution(s) and university(ies). We did not make a distinction if there were more than two institutions of the same type collaborating. For example, both the collaboration between two firms and one between four firms are classified as FF[8].

=== Insert Table 1 around here ===

In the analysis of the following sections, we focus on the non-collaborative and collaborative cases in which at least one firm is involved; in other words, we limit our analysis to F, FU, FP, FF, FUP cases. This is because patenting is basically an activity of firms. Moreover, our purpose is to investigate the causes and consequences of collaboration from the firms' point of view. There are 15 043 such patents out of a total of 15 463 patents, so most of the available data are utilized in the next sections.

3. Basic facts on collaborative R&D in RT

3.1 Evolution of the share of collaborative R&D

Among these 15 043 RT-related patents, which were applied for in Japan between 1991 and 2004, 13 707 (91%) were applied for by only one company. Therefore, the amount of collaboration is strictly limited. However, if we look at the evolution between 1991 and 2004, we clearly see a decreasing trend of the "F" type patent - from 92.5% in 1991 to 90% in 2004 - and an increase in the number of cases of collaboration - from 7.4% in 1991 to 9.9% in 2004, or on average, 8.3% between 1991 and 1999, against 9.9% between 2000 and 2004 (table 2).

=== Insert Table 2 around here ===

[8] In our sample, the number of patent applied by each institution varies significantly. There are a lot of firms that have applied less than five patents, and some firms have applied more than hundreds of patents. The most active patenting firms include Matsushita Electric Industrial Co., Ltd (694 patents), Sony (686), Yaskawa (468), Fanuc (434), Toshiba (367), Mitsubishi Heavy Industries (335), Mitsubishi Electric (292), Honda R&D Co. (272), Hitachi (255). The most active patenting university is Tokyo University (24 patents). Also, AIST is the most active patenting public institution with 77 patents applied for the period of 1991-2004.

If we now focus on the 1 336 cases of collaboration between 1991 and 2004, we find that the large majority of collaboration are between 2 or more firms (73%). As for the other cases of collaboration, 18% are between firm(s) and university(ies), 8% between firms and public research institution(s) and 0.6% between university(ies) and public research institution(s), the other cases are negligible [9] [10].

=== Insert Figure 2 around here ===

If we now look at the evolution by type, we discover that collaboration between firms is relatively declining, as is the collaboration between firms and public research institution(s). On the other hand, the amount of collaboration between firm(s) and university(ies) increased, from 14% on average between 1991 and 1996 to 24% on average between 1997 and 2004 (figure 2)[11].

3.2 Identifying the different types of collaboration and of collaborative players

If one analyzes the types of collaboration and of players, a basic stylized fact is the vast heterogeneity. While F-type collaboration accounts for is 89% for the entire period, it ranges from 98% for Matsushita to 68% for Toyota. Companies like Sony Mitsubishi HI or Mitsubishi E are in the average range, whereas companies like Hitachi, Toshiba or Kawasaki HI are much more collaborative and companies like Matsushita EI, Yaskawa, Nissan, Fujitsu, NEC, Honda or Mazda are much less collaborative (in terms of the percentage of F-type patents). Moreover, the behavior of firms varies depending on the type of collaboration (FF, FU, FP).

In the case of FF-type (collaboration between at least two private companies), one can divide the collaborating companies into two categories. The first one is composed of large companies collaborating a lot in absolute terms. They are Hitachi (86 cases of collaboration, representing 24% of the total number of patents), Toshiba (78, 16%), Toyota (78, 28%), Sony (75, 10%), Mitsubishi Electrics Co. (37, 11%). The second type is composed of either companies with very little capability in RT – Chubu Electric Power (100% of the 14 patents are collaborative) – or R&D companies allied with a very large player - Hitachi Keiyo Engineering (91%, 34)[12].

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[9] For these other cases, we include FUP type in our analysis but do not include UU, UP, and PP types.

[10] It should be noted that, regardless of the type of collaboration, the most of the collaborations are conducted by two institutions: 93% in the case of FF, 87% in the case of FU and 86% in the case of FP. Considering the difficulty of collaboration and of sharing property rights between many partners, we find this result is not surprising, and this is consistent with the analysis by Goto (1997).

[11] It has been pointed out that the so-called "corporatization" in 2004 of national universities should have facilitated collaboration between national universities and firms. Our results show that prior to the 2004 reform, national universities (e.g. Tokyo University) had already collaborated a lot with private companies.

[12] Two other important categorizations can be made to analyze FF type collaboration. The first one is the distinction between the collaborations with closely related firms and the collaboration with the other firms. We find that Hitachi, Mitsubishi Electric, and Mitsubishi Heavy Industries collaborate often with the firms in their groups. Yet, Sony, Yaskawa, and Nissan collaborate mostly with firms outside of their groups. However, our analysis did not lead to any clear results and is not reported here. The second important distinction is between

As for FU collaboration, Toyota is the firm that collaborates the most with universities (10 cases). In terms of absolute numbers, it is followed by Tmsuk, Sony, Rhythm Watch Co. (clock and movement maker), Fujitsu, TechExperts Co., Iseki & Co. (manufacturer specializing in farming machinery). If one looks at the ratio of FU type collaboration to the total patents applied by each firm (but confines it to the firms that have more than 10 patents), small firms like Tmsuk (41% of the 17 total patents) or specialized firms like Rythm Watch Co. (70%, 10) are most active in collaborating with universities. Obviously, the motivation of these two types of companies is to look for capacity which is lacking internally and which may be found in universities.

Regarding FP collaboration, companies collaborating the most with public research institutions are respectively Toshiba (21 cases) and Kawasaki Heavy Industries (13). In these two cases, this is clearly the result of the participation of these two companies with many government-sponsored collaborative research projects, especially through NEDO (the R&D agency of METI) programs.

The final question regards the evolution of collaboration: can we observe a similar increase of collaboration for all the firms? This is obviously not the case as the evolution is quite different between the first sub-period (1991-1999) and the second sub-period (2000-2004). It is stable for some companies like Yaskawa (94% of patents for both periods), while some companies like Matsushita EI, Hitachi, NEC, Mitsubishi E or Honda R&D have followed the overall trend towards more collaboration and some others like Toshiba, Toyota, Mitsubishi HI, Nissan, Fujitsu, Kawasaki HI were a lot less collaborative during the second sub-period. One possible reason for this contrasted evolution is that companies like Toyota or Nissan, which have been relatively active recently in RT, in the beginning did not have the potential internally so they learned from others through collaboration, and then developed their own capabilities in-house. Of course, this explanation does not hold for companies like Honda and Toshiba and requires further investigation.

These two stylized facts – increasing collaboration and the heterogeneity of behaviors across firms – constitute the background of our investigation. However, it is not possible to directly examine the factors and reasons behind these facts, as they are the results of very complex processes. Therefore, we will provide an indirect analysis by investigating the motives and determinants of collaboration at the firm level (section 5). A preliminary step is to check if there are objective benefits to collaborating. We investigate this issue by means of a quantitative and comparative assessment of the quality of collaborative and non-collaborative patents (section 4).

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horizontal (among the final product makers) and vertical collaborations (between final product maker and component makers, users). Such a distinction is essential in analyzing the impact of market competition on the practice of collaboration. Unfortunately, our database does not permit us to distinguish them. We found, however, many cases of vertical cooperation (for example between Yaskawa and Toyota, or between Yaskawa and Kyushu Electric) and very few cases of horizontal cooperation.

4. The benefits of collaboration: assessing the quality of patents

In this section we undertake the econometric analysis to test if collaborative research will affect research productivity using the quality indicators of patents. As mentioned in section 2, we focus on patents which are applied for by firms, as the result of both collaborative and non-collaborative R&D. Our goal is to investigate if there are any benefits of collaboration from the firms' viewpoint and how it differs depending on the type of partners.

4.1 Measurement of the patent's quality

It is usually difficult to directly measure the quality of research activities. However, some papers on this topic indicates that the following variables can be used as proxies to measure the quality of research (or the "quality-adjusted R&D productivity"): number of claims, number of forward and backward citations, number of inventors, and number of technological fields of patent (Trajtenberg, 1990; Tong and Frame, 1994; Lanjouw and Schankerman, 2004). In our econometric estimation, these indicators are used as dependent variables[13]. Yet, we regard the number of inventors as a proxy for R&D expenses, and the indicator will be used in some cases as a control variable rather than the dependent variable[14]. The data on citations are only available up to 1997, so the sample periods for the models that include citations span only up to 1997.

We also construct two composite indexes of these indicators, which provide us with richer information than a single indicator. To construct the composite indexes, we follow the technique suggested by Lanjouw and Shankerman (2004). *quality1* is composed of three indicators (claims, number of inventors, and number of technological fields) for the whole period. *quality2* is composed of three indicators (forward citation, backward citation, and claims). As the data concerning citations are only available between 1991 and 1997, this index only spans the period of 1991-1997.

4.2 Econometric estimation – patent level analysis

Our econometric analysis on patent quality is divided into two parts: the estimation based on the patent level observation and the one based on the firm level observation. While the former estimation is thought to examine the direct impact of collaboration on the quality of its research, the latter estimation is expected to capture the spillover effects of collaboration to the collaborating firms.

[13] Each of these indicators has its own characteristics, and it is hard to determine which one is the best measure of research quality. For example, the number of claims is fixed at the time of the application and does not vary over time; however, there is a subjective element to this indicator. The number of forward citations is regarded as a more objective indicator, but there are citation lags. In this context, various authors (e.g. Lanjouw and Schankerman, 2004) suggest using composite indexes, but there is no agreement in terms of the methodology to build these indexes.

[14] The number of inventors per patent is often used as a proxy to measure the scale of a research project and the accumulated level of human capital. This is because the greater the number of inventors, the bigger the research project is. Also, the larger the research project is, the larger the input of funds and human capital (knowledge). Goto et al (2006) and Mariani and Romanelli (2006) use the number of inventors as a proxy for R&D expenses and find that the coefficient of the variable is significantly more positive on R&D productivity.

4.2.1 Model －patent level estimation

We will first estimate the model based on the patent level observation. It is in the form of:

$$quality_{j(i)t} = \alpha_j + X_{j(i)t}\beta + Z_{j(i)t}\gamma + \varepsilon_{j(i)t}$$

Where:

i is the patent number, j is the first inventor (firm name), t is the year.

$quality_{j(i)t}$ is an indicator of the quality of patent i. We use individual indicators such as the number of claims (*claims*), backward citations (*bwd_cite*), and forward citations (*fwd_cite*) and two composite indicators (*quality1* and *quality2*) for this variable.

α_j is the individual effect of the first inventor. $X_{j(i)t}$ is the row vector of dummy variables which are defined for the types of collaborative research (FU, FF, FP, and FUP). Dummy variable *d_fu* takes one if the patent i is FU type. *d_fp*, *d_ff*, *d_fup* are specified in the same way. If an estimated coefficient for one of these dummy variables is positive and significant, we can infer that the collaboration type which is captured by this dummy variable positively affects the quality of patents.

$Z_{j(i)t}$ is the row vector of control variables, which may affect the quality of patents. These variables include the number of backward citations (*bwd_cites*), the number of forward citations (*fwd_cites*), the number of technological scopes (*techscopes*), and the number of inventors (*inventors*) which is a proxy for the scale of a research project and the accumulation of human capital. We selectively include these variables depending on the nature of the dependent variables. For example, when the dependent variable is *quality1*, we include backward and forward citations as explanatory variables but not the number of technological scopes. We also include year dummy variables (*d_year*).

β and γ are column vectors of estimated parameters.

We apply the OLS estimation for the models of *quality1* and *quality2* and use negative binomial estimation for the models whose dependent variable is the number of claims, backward citations, or forward citations as these data are count data[15].

It appears to be appropriate to apply the fixed effects estimation, as there are unobserved differences in the characteristics of patent applications, number of claims, forward citations, backward citations, inventors, technological scopes[16]. For example, some applicants write the names of all the

[15] We do not use the Poisson estimator, another common estimator for count data. One assumption of the Poisson Regression model is that its mean is equal to its variance. Looking at the characteristics of the data of the number of dependent variables, the observed variances are greater than the means. Thus, the estimation of the Poisson Regression model seems to lead to overdispersion.

[16] This choice is confirmed ex post through a Hausman specification test.

inventors, while others do not. Also, large companies have enough R&D expenses and may have the tendency to allege as many claims as possible, while small companies may not[17].

4.2.2 Results －patent level estimation

The estimation results are reported in Table 3. We get contrasting results between the coefficients in model 1-1 whose dependent variable is *quality1* and models 1-2 and 1-3 whose dependent variable is *quality2*. In the case of model 1-1, we can see that after controlling for the individual fixed effect, all types of collaboration lead to higher value patents. However, if we look at the results on models 1-2 and 1-3, there is no evidence that collaboration leads to increased patent quality. Moreover, in these models, we can see that the number of inventors has a significant impact on patent quality. This result may imply that collaboration will not lead to higher patent quality; instead, patent quality is only affected by the scale of the research, which is usually larger in the case of collaborative than in non-collaborative research. This result is consistent with the findings of Goto et al (2006) and Giuri & Mariani (2005).

=== Insert Table 3 around here ===

If we look at the other models, the estimation results also vary. When the number of claims is a dependent variable (model 1-4), *d_fu* and *d_ff* are significantly positive. *d_fu* is also significantly positive in model 1-5. However, none of them has a significant effect in model 1-6 where *fwd_cite* is a dependent variable. We infer that this non-significant effect on *fwd_cite* might have cancelled out the positive effect on the *claims,* leading to the non-significant results in models 1-2 and 1-3 where *quality2* is the dependent variable.

Thus, the estimation of our patent level analysis above provides different results depending on the model, and it is hard to reach a firm conclusion. One way to attain a final assessment is to follow Lanjouw and Schankerman (2004), which states that the most important quality index seems to be *claims.* Based on this standard, it is possible to argue that collaboration leads to higher quality patents, as suggested by the results of model 1-4. However, we cannot abandon the conclusion that only the scale of the research has an impact on the quality of the patents, as suggested by models 1-2 and 1-3. Thus, a proper assessment of the estimation results at this stage would be that there is limited evidence that collaboration generates higher patent quality.

[17] The fixed effects appear to be arised from the characteristics of "first applicant" because property rights of patents belong to applicants. Yet we specified the model capturing the fixed effects of "first inventor". This is because data concerning the applicants are incomplete in our database (especially Standardized Data), while there appears to be a few errors in "first inventor" (the firms they belong to). The "first inventor" would be a proper proxy for the "first applicant" since the firms that the first inventor belongs to are usually the first applicants.

4.3 Econometric estimation – firm level analysis

The results of the preceding section do not provide unequivocal support for the benefits of collaborative R&D. It should be noted, however, that the estimation based on the patent level data only captures the direct impact of collaboration on the research (or patent) quality and does not capture the spillover effects (or indirect effects) of collaborative research. Spillover effects can come from the close contact among researchers in collaborative R&D, which is likely to transmit novel and tacit knowledge. From these close relationships, firms can gain access to the complementary knowledge and expertise that their partners have and may become more innovative. In this section, we will try to examine the spillover effects of collaborative research, in estimating various models at the firm level.

4.3.1 Model －firm level estimation

For the estimations in this section, we use *quality2, claims, bwd_cites,* and *fwd_cites* as the dependent variables. These variables can be interpreted here as quality-adjusted R&D productivity of firms rather than the quality index of patents. In the case of the model of *quality2*, we use the fixed effect OLS estimation. For the models of *claims, bwd_cites,* and *fwd_cites*, we conduct negative binomial estimations because the dependent variables are count data. In this case, Poisson estimation is not appropriate because of the over dispersion problem. We generalize the Poisson model by introducing an individual and unobserved effect into the conditional mean:

$$\lambda_{it} = \exp[X_{it}\beta + \varepsilon_{it}]$$

Where *i* is firm, *t* is the year. A gamma distribution is usually assumed for $\exp(\varepsilon_{it})$. Explanatory variables include *inventors* (a proxy for R&D expenses), *coinv_ff* (number of FF patents), *coinv_fu* (number of FU patents), *coinv_fp* (number of FP patents).

4.3.2 Results －firm level estimation

The results are summarized in table 4. They vary depending on the model[18]. In model 2-1, where *quality2* is the dependent variable, only the coefficient *coinv_fp* is positively significant (at 1% significance level), while collaboration between firms seems to significantly lead to lower quality-adjusted productivity. If we look at the results on the individual indicators, we can see that *coinv_ff* and *coinv_fu* have significantly positive effects on *claims* (model 2-2), and *coinv_fu* and *coinv_fp* have significantly positive effects on *bwd_cites.* In these cases, collaboration increases the quality-adjusted R&D productivity of firms.

[18] In this section, we do not use *quality1* as a dependent variable because this composite index includes the number of inventors, which is also an explanatory variable.

=== Insert Table 4 around here ===

On the contrary, in the case of model 2-4, when *fwd_cite* is the dependent variable, there is no significant coefficient for collaboration variables. This non-significant effect on *fwd_cite* probably cancels out the positive effect on *claims* and *bwd_cites* in model 2-1, which is probably the reason for the non-significant results when *quality2* is the dependent variable.

However, there seems to be a problem of multicollinearity between *inventors* and *coinv_ff* (the correlation coefficient is 0.57 in this case but only 0.17 in the case of *coinv_fu* and 0.31 with *coinv_fp*). Accordingly, we exclude *inventors* in the estimation[19]. The results are shown in the last column (model 2-5). In this case, we find that all types of collaboration have a significant positive impact on *fwd_cite* (at 1% significance level for the case of FF-type collaboration and at 10% significance level for other cases).

Thus, models 2-1 and 2-4 can be regarded as inappropriate. If we focus on the results of the other three models, we can see that collaboration has significant positive effects on the quality-adjusted productivity of firms. For models 2-2 and 2-3, this is the case even after controlling the scale effects of research (reflected on the coefficient of *inventors*). We find that *coinv_fu* is significant in all three models, while *coinv_ff* is not significant in model 2-3 and *coinv_ff* is not significant in model 2-2. Thus, evidence that FU-type collaboration increases research productivity is more apparent than the other two types of collaboration. Also, research productivity elasticities to the participation of collaboration (results are not reported here) are larger for FU- and FF-types than FP-type collaboration, indicating that the former two types of collaboration yield a greater impact on research productivity than the latter type.

In conclusion, we find that there are significant spillover effects of the collaboration to the institutions that engage in collaborative research, while the estimations of the previous section reveal limited evidence that collaboration directly increases the quality of the research carried out.[20]

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[19] The problem of multicollinearity appears to exist in other models, but we include the number as an explanatory variable to control for the scale effect. The key point here is that the coefficients of the *coinv_ff, coinv_fu, and coinv_fp* are still significant even when the number of inventors is included, except for model 2-4. This is not the case for the patent level estimation, where the dummy variables become insignificant in many cases when the number of inventors is included, due to the problem of multicollinearily.

[20] We also estimate the models using stock variables of collaborative research to test if past experiences of collaboration increase the quality of research. We find that past experiences do not have a significant positive impact on R&D productivity except for past FP type collaboration, which has a positive impact on the number of claims.

5. Analysis on the determinants and motives for collaborative research

Having investigated the benefits of collaboration from the firms' point of view, we turn to the analysis on the determinants and motives of collaborative research. Before describing our empirical test, we briefly review the theoretical and empirical literature on this topic.

5.1 Literature review: theoretical and empirical research

One can group the related theoretical literature into three categories: industrial organization, transaction costs, and strategic management theory (or capability theory), even though they are neither mutually exclusive nor collectively exhaustive (Kogut, 1988; Hagedorn et al., 2000; and Belderbos et al., 2004). We briefly review the industrial organization and capability theories here, but do not cover transaction cost perspective, since we do not include this element in our econometric estimations[21].

Industrial organization literature has emphasized the existence of knowledge spillovers as an incentive as well as a disincentive for engaging in collaborative research. Incoming spillovers are a major incentive for firms to engage in collaborative research. On the other hand, there are outgoing spillovers, which may increase free riding problems. Outgoing spillovers may decrease the attractiveness of cooperation. Recent papers in this field underline that firms can control spillovers, thus minimizing outgoing spillovers while maximizing incoming spillovers. A key factor for controlling spillovers is the level of absorptive capacity of the firm, as higher absorptive capacity brings about firms' ability to utilize external knowledge more effectively. Finally, it has been suggested that the effects of spillovers on cooperation also depend on the types of potential partners. For example, in the case of horizontal cooperation, where competing firms collaborate, higher product market competition is thought to decrease incentives to cooperate. When firms are less direct competitors or in the case of vertical cooperation with suppliers, the likelihood of cooperation does not appear to be associated with any critical level of spillovers.

Resource based view of strategic management perspective - also known as capability theory - claims that each firm has different capabilities and it is costly to create and maintain capabilities. Cooperation can be seen as a means to effectively combine the capabilities of other firms by utilizing their complementarities. According to this argument, institutions will have an incentive to collaborate when their capabilities are different and potentially complementary.

Beyond these three major theoretical explanations, there are other factors that affect the probability of collaboration, which we observed in the recent literature. We describe two of them here. First, the more science based the research topic is, the more complex the research is, and therefore the more collaboration is required. This aspect is thought to be an important reason for the increase in

[21] One reason for this is that our definition of collaboration is not consistent with the distinctions between internalization, research partnership, and market transaction, which are addressed in TC theory. Indeed it appeared to be quite difficult to directly test the TC theory, and there are no systematic quantitative researches on this topic. Odagiri (2003) provides the test of TC theory that is quite specific to see the cases of collaboration with foreign firms as opposed to domestic firms as a counter argument to the TC theory.

collaborative research in the world since the 1970s (Hagedoorn, 2002; Tether, 2002). Second, past experience of collaboration could be an important factor which affects the probability of future collaboration (Gulati, 1995). We readily incorporate these factors into our econometric models.

The empirical literature on this issue can be categorized as either analysis based on large-scale questionnaire surveys or based on very specific case studies which look at a few firms (Hagedoorn et al, 2000). There are contradicting results and therefore more empirical research using different databases has to be carried out. Examples of this type of research include the following studies. First, although most studies give the impression that R&D cooperation occurs mainly in high-tech sectors and between large and oligopolistic firms, Kleinknecht and Reijinen (1992) show it is a much more widespread phenomenon, based on a large dataset representative of a national economy (the Netherlands). Second, Fritsch and Lukas (2001), based on a sample of 1 800 German manufacturing enterprises, identify a set of variables (e.g. size, share of R&D employees) that distinguish firms cooperating on R&D from firms that do not. They conclude that it is more or less the same for cooperative relationships with different partners. But Belderbos et al. (2004) argue that the determinants of R&D cooperation differ significantly across the different types of cooperation: for example, the positive impact of firm size and R&D intensity is weaker in the case of cooperation with competitors. Third, while Belderbos et al. (2004) focus on spillover effects and their results support IO perspective, the paper by Vonortas (1997) offers strong support to the resource-based view of firms and related management approaches.

5.2 Empirical models and variables

Based on the theoretical discussion on collaboration above, we specify the empirical model to examine the determinants of R&D cooperation. Our estimation is based on firm-level data and is in the form of:

$$coinv_{it} = \beta_0 + \beta_1 spillpool_{it} + \beta_2 patStock_{it} + \beta_3 techproximity_{it} + \beta_4 science_{it} + \beta_5 coinvstock_{it} + \mu_{it}$$

where

$coinv_{it}$ is the number of collaborative patents by firm *i* in year *t*.

$spillpool_{it}$ is the spillover pool of firm *i* in year *t*. We use the framework suggested by Jaffe (1986) to calculate this variable.

$patstock_{it}$ is the accumulated number of patents applied by firm *i* before year *t* with the depreciation rate of 10%. This variable is considered to be a proxy to measure the absorptive capacity of the firm. *spillpool* and *patstock* are the variables used to test the Industry Organization arguments.

techproximity$_{it}$ is the index of technological proximity for the collaborative partners. The proximity between two firms is calculated based on the framework suggested by Jaffe (1986)[22]. This variable measures the similarity in technological fields among firms which engaged in collaborative R&D. We include this variable to test the capability theory; negative coefficients for this variable will indicate the consistency with capability theory.

science$_{it}$ *is* the number of patents in the "science-based" technologies among the sub-types of RT technologies[23]. We assume that R&D activities in science-based technology are more complex and exert more uncertainty. Therefore, more collaboration is expected.

coinvstock$_{it}$ is the accumulated number of collaborative patents of firm *i* before year *t.* This variable is used to test if past collaborative experience affects the tendency of collaboration in the future.

We also consider the heterogeneity in the determinants of collaboration among the different types of collaboration: FF, FU, and FP (which include FUP). In other words, we regress the explanatory variables discussed above against the following variables and test if and how the determinants of collaboration differ among these cases. Alternative dependent variables are therefore as follows:

coinv_ff$_{i}$: number of FF-type collaborative patents of firm *i* and time *t*.

coinv_fu$_{it}$: number of FU-type collaborative patents of firm *i* and time *t*.

coinv_fp$_{it}$: number of FP-type collaborative patents of firm *i* and time *t*.

5.3 Empirical results

The results are reported in table 5. We used Random Effect Tobit estimation for models 3-1a, 3-3 and 3-4, as the dependent variables have many zero values and they appear to be left censored. We use the Negative Binomial estimation for 3-1b and 3-2, as the observations do not contain many zeros. The first and second columns of the table (models 3-1a and 3-1b) depict the results of the regression for all collaborative patents. It shows that the coefficients of s*pillpool* and *patstock* are positive and statistically significant. Therefore, IO arguments seem to be relevant in the most general case, when

[22] In order to calculate the technological proximities, it is necessary to have more than a few patents for each firm. Thus, we restricted our sample to firms that applied for more than five RT-related patents in the sample period. This restricted sample still covers 70% of collaborative research in our whole sample; so it does not seem to cause a severe sampling error.

[23] We follow the classification defined by JPO to identify the science-based technologies. According to JPO, science-based technologies in RTs include five sub-types of 26 sub-types of all RT. It is interesting to see that the number of patents in only three of these categories (mobile robots, sound recognition, and image processing) have increased during our sample period while the number of patents in other technologies have decreased or have not changed. These three are among the five science-based technologies which are also closely related to the development of next generation robots. Thus, the increase in the number of patents related to next generation robots might be associated with the increase in collaborative R&D. Yet it is worth noting that the classification by JPO (2002) is quite descriptive and unsystematic. Contrary to classical studies in this field (e.g. Gemba et al, 2005), it does not rest on the construction of a science linkage index. This is based on interviews of experts in the field and on the recognition that the published academic articles in these fields have increased drastically recently.

one does distinguish among different types of collaboration. The coefficients of other variables show different results depending on the model.

=== Insert Table 5 around here ===

The next three columns in the table show the results of models 3-2 to 3-4 where the dependent variable is FF, FU, and FP-types of collaboration respectively. There are clear differences in the results among the different types of collaboration. First, the coefficients of the *spillpool* and *patstock* are positive and significant in the case of FF-type collaboration (model 3-2). This is consistent with the hypothesis of IO theories. However, they are not significant in models 3-3 and 3-4 (in the cases of FU and FP): IO arguments do not hold in these cases. Moreover, the coefficient of *techproximity* is negative in the models of FU and FP, indicating that institutions whose technological position differs are likely to be partners. This result is consistent with the hypothesis of capability theory[24].

Furthermore, the coefficient of s*cience* is positive and significant (respectively at 1% and 10%) in the cases of FU-type collaboration (model 3-3) and FP-type (model 3-4) but is not significant in FF-type (model 3-2). Thus, firms that engage in more science-based technologies appear to be more active collaborating with universities and public research institutions. This may be reflected by the fact that universities mostly engage in science-based research while research in firms mostly involves applied technologies. In other words, firms appear to collaborate with universities in order to acquire complementary knowledge, which again seems to support the validity of capability theory in the case of FU-type collaboration.

Finally, the coefficient of *coinvstock* is negative and significant in the case of FF-type collaboration (model 3-2) but non-significant in the case of FU-type collaboration (model 3-2) and positive and significant in the case of FP-type (model 3-4). It shows that only in the case of industry-government collaboration, that past experience in collaboration affects the probability of future collaboration. However, its coefficient is negative in model 3-2. It is hard to interpret this result, and further research is needed on this point.

To sum up, we find that the determinants and motives for firms to engage in collaborative research significantly differ depending on the partner.[25] With regard to collaboration among firms, potential spillover and absorptive capacity are key determinants, and IO theories appear to hold in this

[24] On the contrary, the coefficient of *techproximity* is non-negative in model 3-2 (FF-type), indicating that capability theory is not valid for collaboration among firms. This result is not easy to interpret but it may suggest that collaborative research among firms does not bring about "beneficial" cooperation in the sense of access to complementary external resources, and there may be some factors that hinder such beneficial cooperation. For example, rivalries among firms on the market and high coordination costs prevent the likelihood of cooperation among firms, as key sector players explained to us during interviews. We did not include these factors in our analysis here, but it appears to be worthwhile to examine this point further in the future.

[25] Therefore, the results obtained without distinguishing the type of partner should be interpreted very cautiously: in our case, the fact that IO is validated at this general level may come from the fact that collaboration among firms is much more numerous than other forms of collaboration.

case. Yet, in the cases of collaboration with universities or public institutions, firms appear to seek complementary knowledge or capabilities of their partners and capability theory seems to be appropriate in these cases. These results may partly explain the stylized facts in section 3. As RT becomes more and more science based with the development of technologies such as mobile robots, artificial intelligence, image processing or sound recognition, universities appear to be a more and more attractive partner for firms to collaborate with. It may explain why FU-type collaboration has increased since the mid-1990s, as universities have capabilities in some specific fields. The heterogeneity of the behavior of firms in terms of collaboration is a very complex question whose answer requires opening the black box of R&D decision making at the level of the firm. Our results, however, suggest that it depends heavily on the accumulation of capabilities within the firms. For example, the high level of collaboration of Toyota with universities can be explained by the fact that it was a late comer in this technology and its goal has been not to improve existing technologies at the margin but to develop frontier technologies.

Conclusion

In this article, we have investigated the issue of collaborative R&D by using patent data and by focusing on the information concerning inventors. Patent data are very valuable as a complement to other data like questionnaire surveys. They are less biased regarding the size of the institutions. They are objective as they do not depend on the opinion of a manager. They are also particularly appropriate to analyze the benefits of collaboration. However, to avoid an underestimation of the collaborative cases, it is preferable to focus on the information regarding the inventors rather than the applicants. As the institutions to which the individual inventors are affiliated are not systematically indicated, it implies very time consuming preliminary work. In these conditions, we restricted our analysis to the case of the robot technology in Japan from the 1990s. At this stage, the type of research we conducted in this paper is only a case study. However, as these data are relatively homogeneous across countries and technologies, it should be very fruitful to extend our research to make other comparisons.

In the case of robot technology in Japan, we can summarize our findings as follows:

- The level of collaboration was initially very low but slightly increased between 1991 and 2004, essentially due to the development of industry – university collaboration;
- Generally speaking, from the point of view of firms, collaboration in patenting seems to lead to a higher level of quality of the invention, when one takes into account the spillover effects. The direct effect is less clear;
- As for the determinants and motives of collaboration from the viewpoint of firms, it varies depending on the type of partner. When it is another firm, the IO argument holds: the existence of spillover and of absorptive capacity plays a decisive role. On the contrary, in the cases of collaboration with

universities or public research institutes, the capability argument, emphasizing the existence of complementarities among partners, is more appropriate.

This study can be enhanced and complemented by further research especially in the following directions. First, it may be interesting to further investigate distinctions between external/internal collaboration (outside/within the group) or horizontal/vertical collaboration within the general category of collaboration between firms. Second, empirical tests should be elaborated to directly test the validity of the predictions of transaction cost theory. Finally, we have mentioned that government – local and central, ministries and related agencies – have been very active promoting collaboration in RT. A study is needed to evaluate the efficiency of government policies using the same patent data, which could be divided into ones related to government sponsored programs and the others.

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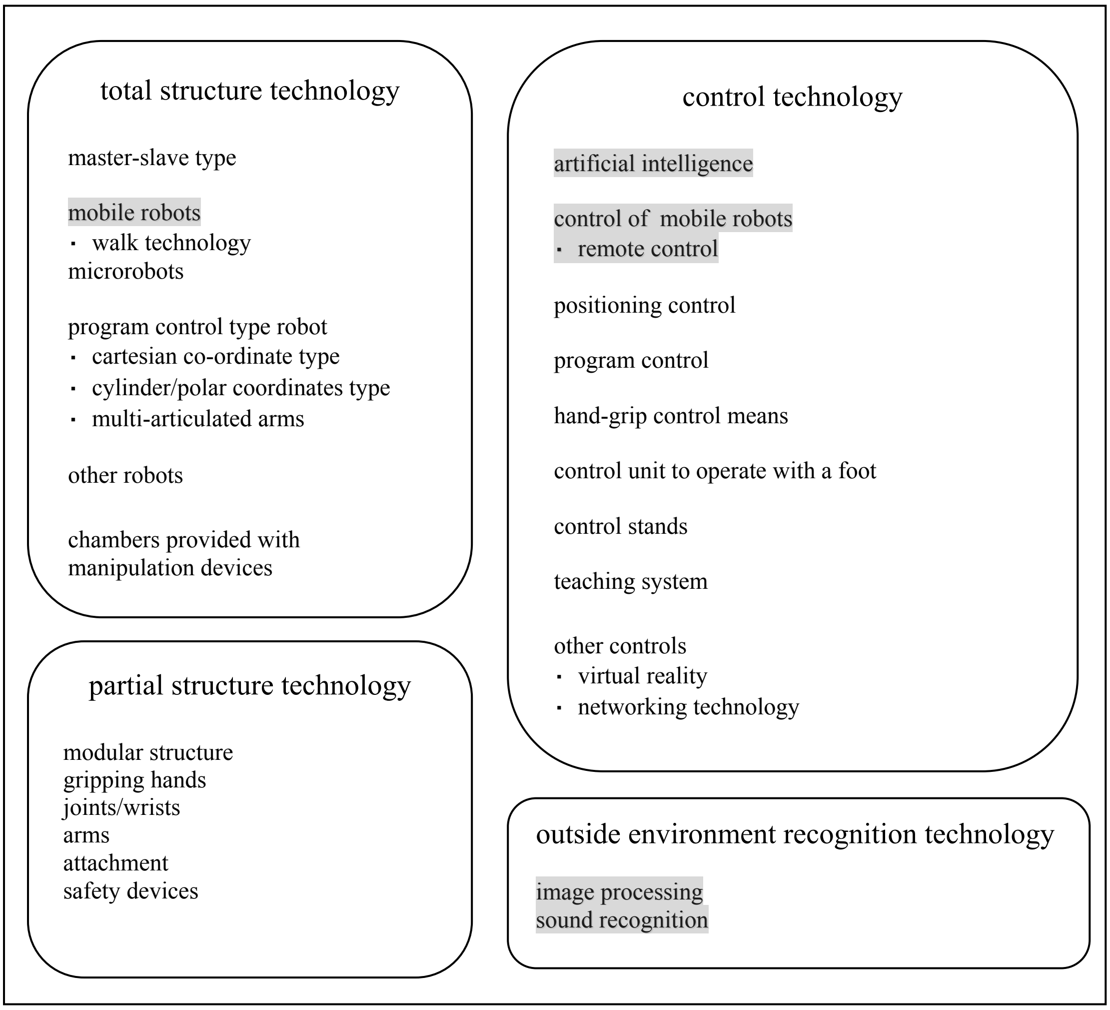
Figures & tables

Figure 1: Four macro classifications and twenty micro classifications of RT



Source: JPO (2002).
Note: The shaded values are closely related to next generation robot technology.

Table 1: Classification of inventions by type of collaboration

F	invention by one firm
U	invention by one university
P	invention by one public research institution
FU	collaboration between firm(s) and university (ies)
FP	collaboration between firm(s) and public research institution(s)
FF	collaboration between firms
UP	collaboration between university (ies) and public research institution(s)
UU	collaboration between universities
PP	collaboration between public research institutions
FUP	collaboration between firm(s), university (ies) and public research instiution(s)

Table 2: Evolution of the number of RT-related patents by type of collaborations and non-collaborative patents (absolute numbers)

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	Total
F	635	1 067	1 326	1 484	1 232	954	949	871	803	962	1 024	821	853	726	13 707
FF	37	61	121	94	119	84	50	50	42	81	78	73	36	50	976
FU	8	15	17	16	24	10	13	14	13	16	22	19	34	23	244
FP	6	5	16	6	9	11	3	8	8	9	9	10	4	4	108
FUP									1	1		4		2	8
Total	686	1 148	1 480	1 600	1 384	1 059	1 015	943	867	1 069	1 133	927	927	805	15 043

Figure 2: Evolution of collaboration involving at least one firm (percentage)

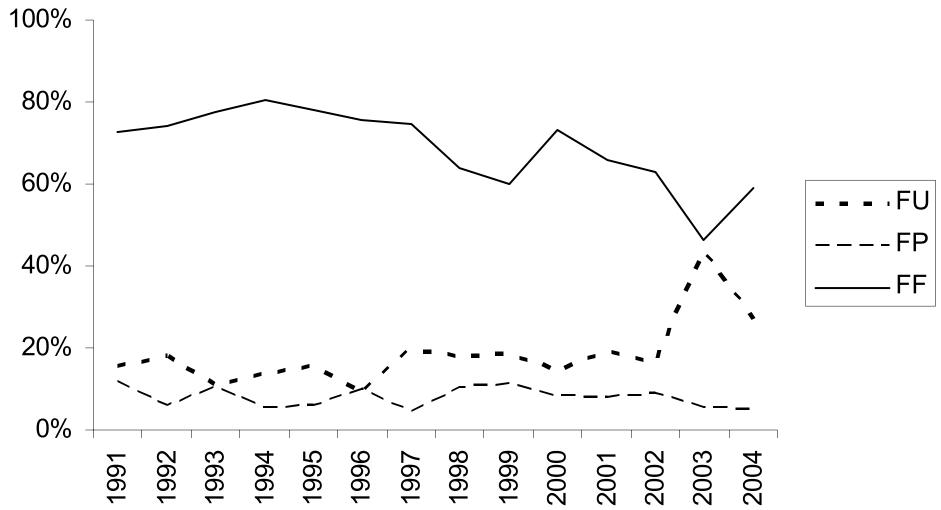


Table 3 The effect of collaborative patents on patent quality

	OLS Estimation-Fixed Effects			RE Negative Binomial Estimation		
	1-1	**1-2**	**1-3**	**1-4**	**1-5**	**1-6**
Dependent Variable	*quality1*	*quality2*		*claims*	*bwd_cites*	*fwd_cites*
Sample Period	1991-2004	1991-1997		1991-2004	1991-1997	1991-1997
d_fu	0.626*** -0.096	-0.062 (-0.198)	0.067 (-0.206)	0.116** (-0.063)	0.369** (0.204)	0.157 (0.257)
d_fp	0.314** -0.152	0.023 (-0.344)	0.115 (-0.333)	-0.039 (0 .101)	0.508 (0.353)	0.205 (0.467)
d_ff	0.541*** (-0.036)	-0.192*** -0.056	-0.035 (-0.051)	0.0520** (0.023)	0.050 (0.068)	-0.022 (0.082)
d_fup	0.325 (-0.243)			-0.387 (0.359)		
inventors		0.089*** (-0.01)				
techscopes		0.032* (-0.018)	0.033* (-0.019)			
constant	-0.308*** (-0.036)	-0.327*** (-0.05)	-0.156*** -0.05	0.743 (0.037)	-0.608*** (.006)	0.336*** (0.075)
d_year	included	included	included	included	included	included
Number of observations	14 813	8 263	8 263	14 813	8 263	8 263
Number of groups	1 597	1 029	1 029	1 597	1 029	1 029
F-test	F(1596,13197)= 2.77 (P>F=0.000)	F(1028,7223)=1 .52 (P>F=0.000)	F(1028,7224)=1 .57 (P>F=0.000)			
Hausman test	chi2(19)=799 (P>chi2 =0.000)	chi2(11)=63(P> chi2=0.000)	chi2(10)=175 (P>chi2=0.000)	chi2(17)=24.9 (P>chi2 =0.092)	chi2(9)=6.84 (P>chi2=0.653)	chi2(9)=11.13 (P>chi2=0.267)

Notes: Heteroskedasticity-Robust standard errors in parentheses. * p<.1; ** p<.05; *** p<.01. *quality1* is a composite index composed of the number of claims, inventors and techscopes. *quality2* is a composite index composed of the number of claims, fwd_cites and bwd_cites.

Table 4 The effect of collaborative patents on quality-adjusted R&D productivity of firms

	OLS fixed effect	Negative Binomial Estimation-Fixed Effects			
	2-1	**2-2**	**2-3**	**2-4**	**2-5**
Dependent Variable	*Quality2)*	*claims*	*bwd_cites*	*fwd_cites*	*fwd_cites*
Sample Period	1991-1997	1991-2004	1991-1997	1991-1997	1991-1997
inventors	0.028 (-0.323)	0.0086*** (-0.0004)	0.0138*** (-0.0011)	0.0118*** (-0.0013)	
coinv_ff	-0.309*** (0.119)	0.0265*** (-0.0073)	0.0228 (-0.0172)	0.0005 (-0.0179)	0.0854*** (-0.0152)
coinv_fu	-0.109 (0.415)	0.2265*** (-0.0343)	0.1951** (-0.0935)	0.1174 (-0.0836)	0.1726* (-0.0889)
coinv_fp	0.150*** (0.551)	-0.0046 (-0.0453)	0.1694** (-0.0788)	0.0637 (-0.0834)	0.1626* (-0.0885)
constant	-0.273 (0.323)	0.2078*** (-0.072)	-0.2475** (-0.1039)	0.8915*** (-0.1325)	0.8949*** (-0.1316)
d_year	included	included	included	included	included
Number of observations	2 358	3 283	1 408	1 307	1 307
Number of groups	1 213	704	359	320	320
Sample periods	1991-1997	1991-2004	1991-1997	1991-1997	1991-1997
Log-likelihood		-8 202.27	-2 229.24	-1 458.31	-1 486.16
Hausman test	chi2(10) = 21.41(P>chi2 =0.0184)	chi2(17)=40.67 (P>chi2 =0.001)	chi2(10)=66.21 (P>chi2=0.000)	chi2(10)=86.29 (P>chi2=0.000)	chi2(9)=107.32 (P>chi2=0.000)

Notes: Heteroskedasticity-Robust standard errors in parentheses. * p<.1; ** p<.05; *** p<.01. *quality2* is a composite index composed of the number of claims, fwd_cites and bwd_cites.

Table 5: Determinants of collaborative patents

	3-1a	3-1b	3-2	3-3	3-4
Dependent Variable	***coinv***	***coinv***	***coinv_ff***	***coinv_fu***	***coinv_fp***
	RE Tobit Regression	FE Negative binomial Regression	FE Negative binomial Regression	RE Tobit Regression	RE Tobit Regression
spillpool	0.0038*** (0.0009)	0.0024* (0.001)	0.0023* (0.0011)	0 (0.0009)	0.0019 (0.0013)
patstock (10%)	0.0155*** (0.0029)	0.0059*** (0.0011)	0.0068*** (0.0013)	0.0027 (0.0023)	0.0021 (0.0032)
techproximity		0.6264* (0.2881)	1.0324** (0.3398)	-2.4495*** (0.6712)	-1.7445* (1.0129)
science	1.0432*** (0.2425)	0.0564 (0.1552)	0.0348 (0.1721)	0.9553** (0.3546)	0.1622 (0.5336)
coinvstock (10%)	-0.0009 (0.0205)	-0.0424*** (0.0061)	-0.0471*** (0.0071)	-0.0098 (0.0147)	0.0464** (0.0179)
constant	-3.7205*** (0.4889)	4.3005 (7.0343)	1.596 (0.9119)	-0.7907 (0.7348)	-1.8548 (0.9404)
d_year	included	included	included	included	included
Number of observations	2 329	521	498	582	582
Number of groups	316	118	109	179	179
Log-likelihood	-2 532.9020	-608.9391	-584.1486	-415.7775	-224.5662
Likelihood-ratio test comparing model against pooled tobit model	chibar2(01) =156.99 (Prob> 0.000)			chibar2(01) =11.55 (Prob> 0.000)	chibar2(01) =4.75 (Prob> 0.015)
left-censored observations	1 588			460	527
Hausman test		chi2(17)=506.16 (Prob> 0.000)	chi2(18)=35.84 (Prob> 0.0074)		

Notes: Heteroskedasticity-Robust standard errors in parentheses. * p<.1; ** p<.05; *** p<.01.