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Academic patenting and the scientific enterprise: Lessons from a Japanese university

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Abstract

In this paper, we study the influence that academic patenting has on faculty members belonging to a research intensive Japanese university. We intend to contribute to the literature on both the use of patenting in academia and the influence it has on a researcher's agenda setting. First, we document how recent policy changes have favored an increasing use of patents by faculty members in Japan. Then, using two complementary set of data, cross-section and panel data, we focus our attention on three main dimensions: the effect of patenting on academic productivity measured in terms of publications and their quality; the role of financial factors; and the influence of peer effects. Our main findings are the following. First, we find that patenting and publishing were complementary activities in our two empirical settings. Moreover, we find that the output of colleagues working in the same department influences a researcher propensity to patent. The results show as well that the amount of contractual research funds received by a researcher is positively correlated with his/her number of patents, while the number of research grants - not the amount - is correlated to his/her patenting output. Finally, another interesting result concerns the influence of a researcher's age on his/her propensity to patent.

Keywords: Academic patenting, peer effects, intellectual property rights, technology transfer, university-industry relationships, Japanese innovation system

JEL classification: O3

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1 Introduction

Recent work on universities has led many scholars to investigate the consequences and incentives behind academic patenting. This stream of literature began in response to the enactment of the Bayh-Dole Patent and Trademark Amendments Act of 1980, which allowed American universities to receive patents and grant licenses from research funded by the federal government. The number of patents granted to American universities has peaked in 2002 at just under 3,300, compared to 300 in the seventies. The biomedical related patent classes dominate these awards (National Science Board, 2008). Most observers attribute this tendency to the legislative change, but it is worth noting that the trend preceded the Act: Colyvas et al. (2002), based on case studies, argue that two other factors could explain the surge. First, the period saw the rise of important new areas of university research, namely molecular biology and computer science; both of which are of particular interest to the industry. Second, over the same period, various patent offices extended the range of research results that were patentable (Jaffe and Lerner, 2004). According to Colyvas et al. (2002) these two elements led to the increase in patenting and licensing, the principal effect of the Act being to accelerate these trends.

The increasing reliance on patenting raised many questions in the literature. The enthusiasts spoke with emphasis of the increasing role of universities in economic development. The "Triple Helix" concept (Etzkowitz, 2003) sees patenting by universities as an indicator of their new involvement in the commercialization activities, beyond the traditional role of research and teaching. In the same vein, Jensen and Thursby (2004) show that the direct involvement of scholars has proven to be a determinant in the success of technology transfer. Skeptics, by contrast, consider that the increase in patenting and commercialization activities by universities could lead to some caveats. The industry may use its growing relative importance to shape research agendas, inducing a redistribution of resources from basic to applied research. Other possible adverse effects of academic patenting include potential conflicts of interest, secrecy issues, delays in the publication process and increased costs of research (Heller and Eisenberg, 1998). A growing "anti-commons" perspective highlights the negative role of Intellectual Property Rights (IPR) over scientific knowledge (Davis et al., 2011). Academic inventors may have to use patents to protect and exchange their new knowledge. In that respect, patenting is seen as a defensive mechanism to enable the diffusion of knowledge. This new situation may create tensions within the academic community, and may be less efficient in term of fast diffusion and validation of knowledge than the previous one relying on pure "open science" because of the transaction and maintenance costs associated with patenting (David, 2011). A large number of studies has examined the impact of patenting activity on academic research; while the majority of the research has been centered on the US and Europe, very little has been said about Asia.

The aims of this paper is to assess how academic patenting is related to academic science with three dimensions in mind: the effect on academic productivity measured in terms of publications and their quality; the role of financial factors and peer effects in determining the relation between patenting and publishing; and finally the effect of institutional and legal changes in shaping the decisions of academics. In order to achieve this, we examine closely the Japanese case and provide an analysis of a leading Japanese research university, Tohoku University. To our knowledge there is no study available in English or Japanese on this topic centered on the recent Japanese context. In order to achieve this goal, we take advantage of the availability of patent and publication databases together with data collected on individual faculty members at Tohoku University.

Our core research question is to see whether patenting and publishing activities are complementary or substitutive. In this respect, we take into consideration two complementary dimensions: the link between individual and collective determinants of faculty research productivity, and the varying influence of diverse types of funding schemes. Nevertheless, we are aware that academic patenting is not the only mechanism, not even the main one, of knowledge exchange between the academics and the industrial world, neither that it symbolizes the full range of technology transfer activities, other mechanisms such as consulting, training, contract research, meetings, conferences or the creation of physical facilities are present. However, we weigh this enfeeblement by the strength patent carries: their availability and their epitomization of commercial activities by academia.

This paper is organized as follows. Section 2 lays out a brief description of the Japanese case in terms of institutional reforms and their links to academic patenting, before moving to a description of the Tohoku university case. In Section 3, we first state our research questions and hypotheses. Our empirical work is based on two complementary research designs. Section 4 presents the results of a pooled cross section analysis of a large sample of faculty members from 2004 to 2007. Section 5 is based on a panel dataset focusing on a group of early adopters of IP related activities that have been active patentees before 2004. We then summarize the main results of the empirical work and finish with a general discussion.

2 The Japanese context

The goal of this section is to give a concise account of the Japanese reforms that were implemented in recent years to facilitate the commercialization of university inventions. The main point here is to highlight how these reforms, and particularly the Incorporation of national university in 2004, have paved the way for a dramatic increase in academic patenting. We, then, move to a short description of Tohoku university's case – our unit of analysis – to show how the university has embarked vigorously in this trend, by being at the forefront of academic patenting in Japan.

2.1 University reform and IP management

In Japan, university-industry collaboration has evolved recently in order to facilitate interaction between the two institutions. Until 1980, restrictive government regulations caused levels of university-industry collaboration to remain low. In 1983, the Ministry of Education relaxed its regulations, and notably allowed national universities to cooperate with industry. However, it is only after the introduction of the 1995 Science & Technology Basic Law and the 1998 Technology License Office (TLO), which legitimized and facilitated transparent and contractual transfers of university discoveries to industry, that universities started to cooperate actively with industrial partners. Two other Laws had important effects. In 1999, the Japanese equivalent of Bayh-Dole Law was enacted. And in 2004, the Japanese government incorporated the national universities as "independent administrative entities."[1] Since 2004, the universities have gained greater autonomy. For instance, they can maintain the ownership of their invention - which was seldom the case before the Incorporation- and manage directly their relations with outside partners (Takahashi and Carraz, 2012).

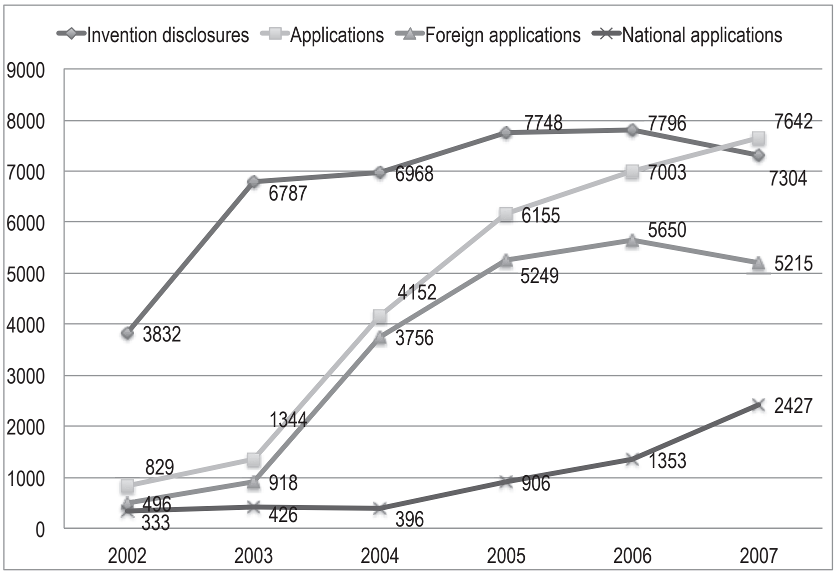

Figure 1: Invention disclosures and patent applications by national universities. *Source*: Compiled from various documents on the MEXT website.

Figure 1 shows the influence of these changes in the legal environment on invention disclosures and patent applications. Invention disclosures have started to rise before the Incorporation, with a strong increase from 2002

[1]For a more detailed account of the process that led to the Incorporation one can refer to Harayama and Carraz (2008).

and 2003, preceding the increase of patenting. Shortly, thereafter the figures only slightly increase indicating a kind of plateau around 7,500. As for patent applications, the numbers skyrocketed in 2004, and increased steadily thereafter. In 2007, the number of national patent applications decreased for the first time, while the number of foreign applications intensified. These figures indicate two tendencies: first the Incorporation entailed a huge increase in IPR activities; second, in 2007-8, the numbers seem to have reached a peak. Furthermore, universities appear to have gained expertise and improvement in the quality of their applications as the number of national applications decreased while foreign ones increased in 2007. Foreign applications are often considered to be more valuable to the applicant as they cost more to start and maintain.

This trend is not specific to Japan. Universities all over the world are increasingly patenting the outcome of their research (Geuna and Nesta 2006; Mowery et al., 2001). Our data shows that Japan is also following this upward trend. Together with research and teaching, universities are considered the generators of future economic growth. Technology transfer to the private sector has clearly become a desirable outcome of academic research. Nowadays, Japanese universities directly manage their IPR, and thus are more prone to facilitating and advertising the number of patents their faculty can produce.

The university administration is clearly gearing up in IP management. But what about the figures, do they lead to an increase of patenting in all the university or is it only happening in some institutions? Figure 2 shows the number of patent applications by Japanese universities in terms of patents per year: in 2003, 61 universities had applied for 1 to 9 patents, a number that rose to 115 universities in 2005. The tendency is the same for the highest bracket: in 2003, only one university applied for more than 200 patents, in 2005 there were 7. This illustrates the fact that universities quickly embraced the use of patents, at both ends of the spectrum. However, we should remain cautious about the total increase of patents applied by Japanese universities; universities not previously active in patenting account for a significant part of the growth in overall university patenting. This phenomenon has been similar in the US in the 70s, as noticed by Mowery et al. (2001).

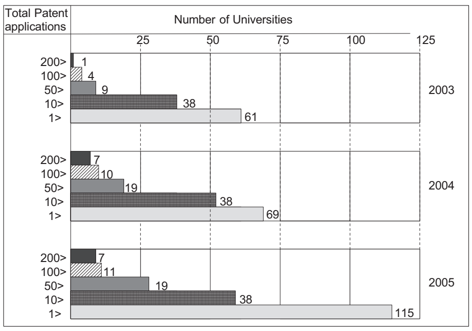

Figure 2: Patents applied by Japanese universities according to frequencies. *Source*: UTTA (2007).

2.2 Tohoku University

2.2.1 A short presentation

In this section we briefly present our unit of analysis, Tohoku University, and provide figures on the recent trends in its patenting activity. Tohoku University is a Japanese national university based in Sendai, Japan. Tohoku University was founded in 1907 as the third Imperial University of Japan, following the Tokyo Imperial University and Kyoto Imperial University.

It is recognized on various level as a strong research university; the 2012 Shanghai academic ranking placed it in 5^{th} among Japanese universities, internationally ranking it 23^{rd} in the field of engineering and technology, and 46^{th} in natural sciences. Additionally, Tohoku University is ranked 3^{rd} in material science and 13^{th} and 22^{th} in physics and chemistry respectively in the Thomson Scientific ESI list of most cited papers worldwide. Some famous discoveries and technological advances made at Tohoku University include the Yagi-Uda antenna (Hidetsugu Yagi and Shintaro Uda in 1925), the pin diode (Jun-ichi Nishizawa in 1952), the principles of perpendicular magnetic recording (Shun-ichi Iwasaki in 1977) for which Koichi Tanaka was awarded the Nobel Prize for Chemistry in 2002.

During the period from 2004 to 2009, 601 faculty members have been listed as inventors on at least one patent applied by the university or the university TLO. This means that approximately 21% of the faculty members have been listed on a patent since Incorporation. As scientists in social sciences and in humanity disciplines seldom do research that lead to patent, the share is bigger if we compare it to the Engineering and Science related faculty members, making the figures jump to nearly 50%. We can compare these figures to similar data available for the Massachusetts Institute of Technology (MIT) where, from 1983 to 1997, approximately half of the teaching staff has been involved in at least one patent (Agrawal and Henderson, 2002). This puts Tohoku University at the same level as an institution widely known for its entrepreneurial and technology transfer activities, and makes it an interesting experimental setting to evaluate the influence of academic patenting on faculty members' research productivity in Japan.

2.2.2 Patenting activity

In order to measure the Tohoku University patenting activity, it is necessary to make a distinction between university-owned patents and university-invented patents. University-owned patents are patents for which the ownership belongs to the university. Unfortunately, data on university-owned patents only offer a relatively comprehensive picture of faculty patenting activity in the US and Canadian cases. In the European setting, at least for the 80s and 90s, this information is less reliable as a majority of the patents invented by academic personal were not applied by the university. Looking at university-owned patents gives a wrong picture of the patenting output of faculty members, it creates a downward bias. This is due to the tendency of European academic researchers to leave the property rights of their invention to the firm that financed the project, while still being included in the list of inventors. To account for this problem, it is necessary to introduce the concept of university-invented patents, which cover inventions by academic scientists, but assigned to the individual scientists, public research organizations and, above all, business companies. Lissoni et al. (2007) suggest that university-owned patents in France, Italy and Sweden represent no more than 11% of all university-invented patents (69% in the US), while business-owned patents represent 60%-80% of the applications (25% in the US).

In the case of Japan, until the Incorporation, university-invented patents were believed to be the norm as the majority of the IPs were transmitted to the companies by-passing the university administration. Kneller (2003) illustrates how a majority of university discoveries were transferred directly from inventors to companies under the disguise of donations, the researcher being listed on the patent application as an inventor. The Incorporation of national universities in 2004 meant that universities would own and enforce all the inventions made by their employees. This mainly explained the strong upward trend of academic patenting for the years 2003-4 in Figure 1.

In the Japanese context, Walsh and Nagaoka (2009) found that Japanese universities, much like European universities, used to own a minor share of their scientists' patents. According to their estimations, before 2004 they reckon that around 83% of university researchers' inventions in Japan were not assigned to the university. Recent reports from the National Institute of Science and Technology Policy (NISTEP) investigate the changes entailed by the policy reforms. Shibayama and Saka (2010), using results from MEXT survey, report that, as of 2007, more than 90% of public universities had formal policies to attribute the invention rights of faculty members to the universities.[2] Kanama and Okuwada (2007; 2008) analyze directly this phenomenon and clearly show the visible trend before and after the Incorporation for three universities: Tsukuba, Hiroshima and Tohoku. We present here their main results for Tohoku University. Nonetheless, it can be noticed that these tendencies are similar for the other two universities.

The researchers (Kanama and Okuwada, 2007; 2008) compare university-invented and university-owned patents for the period 1993-2007. University-invented patents are patents not belonging to the university, but with at least one inventor coming from academia. In order to gather information on inventors, they retrieved from Tohoku University administration the names of all faculty members who reported at least one invention disclosure during the period 1993-2004. Using that list, they searched for all these researchers

[2]The top 100, out of 87 national and 86 public universities, represent the 100 universities that obtained the largest amount of Grant-in-Aid for Scientific Research (i.e. national research grants) in 2007.

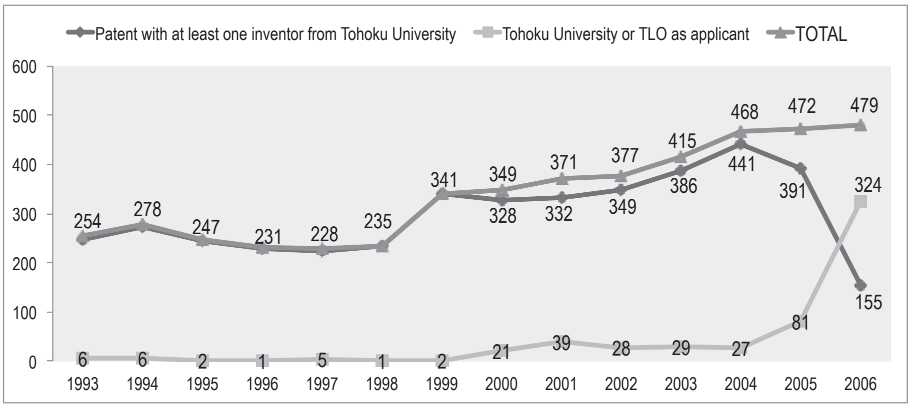

Figure 3: Tohoku University patents.
Note: Adapted from Kanama and Okudawa (2008).

in the inventor section of the Japanese Patent database.[3] The results of this search are presented in Figure 3. The figure describes Tohoku University-owned and invented patents. We see that, up to 1999, university-owned patents were quite inconsequential: the number of patents started to rise in 2000, probably as a consequence of the Japanese Bayh-Dole Act. The figures really show a dramatic increase only after Incorporation. Until 2000, only a minority of the invention disclosures led to a patent application by the university. Alternatively, university-invented patents were quite high throughout the period, with an increase in 1999-2000 and a decrease after 2004 when the university started to manage its IPR more aggressively. Overall, we see from Figure 3 that university members have been active in the IPR business on a long term basis, yet there is a constant increase throughout the period with important changes regarding the evolution of ownership through time, from outside partners (mainly companies) to the university. This result enables us to better interpret Figure 1. The rise of patenting activity in 2004 did not emerge from thin-air: the potential was not laid dormant until 2004, it just took more informal channels to diffuse it.

3 Review and research questions

In the past few decades, universities and other public bodies have become more proactive in their attempt to transfer their scientific discovery. This phenomenon has created a demand for empirical evidence on that matter. In this section, we first provide some evidence from the literature on the relation between patent and publication. We then investigate the influence of peers on these variables. Finally, we present the potential effects of various sources of funding on these variables.

[3]A more detailed account of their approach is given in Section 5.1.

3.1 Patent and publication

The aim of this section is to explore the theoretically conceived dilemma that individual scientists face, namely the potential trade-off between basic research activities and those activities that are required to successfully develop and commercialize academic inventions. In commercial settings, basic research is often considered as a substitute for more applied works. Several observers have worried that a similar dynamic might be at work in universities, despite the fact that the majority of empirical studies found no evidence of a negative impact on patenting activities on publication output. Our objective here is to precisely relate the aspects which are relevant to our inquiry and comment more thoroughly on some comparable works. We present below some of the major empirical findings.

Fabrizio and DiMinin (2008), using a matched panel sample of 150 patenting and non-patenting scientists across several US universities found a positive relationship between patenting and publishing. Azoulay et al. (2006) using a large sample of US life scientists found that patenting has a positive effect on the rate of publication of articles. They used the inverse probability of treatment weight to predict selection into patenting. In a recent study, using the same method on a sample of Max Plank Institute's directors in Germany, Buensdorf (2009) found results consistent with prior findings, that inventing does not adversely affect research output. Exploiting cross-sectional data from a survey of doctoral recipients, Stephan et al. (2007) found patents to be positively and significantly related to the number of publications. Carayol (2007) at the University Louis Pasteur in France, encountered similar results using cross-sectional data. The only major discording voice is the work of Agrawal and Henderson (2002) on a panel of MIT scientists. They found no evidence that patenting activity is significantly correlated to publishing activity.

The empirical evidence points, overwhelmingly, to the direction of a complementary relation. The logical question to ask is, therefore, why should we engage in a similar endeavor? The first response is that, until now, all the studies have been Americano-European centered. To our knowledge no similar research exists in the context of Japan or even Asia. This lack of data on Asia calls for research on that topic: Are there any differences due to different institutional settings, or do comparable results exist? The question calls for an answer. On top of this, we were able to construct a unique dataset on Tohoku University that we believe can be mobilized to better model the determinants of the relationship between patenting and publishing. Building on the data at hands, we want to test the hypothesis that patenting and publishing activities are complementary activities.

3.2 Influence of peers

One important factor in determining whether a scientist is likely to engage in any technology transfer activities is the influence of peers in shaping his choice. Indeed, science is not a solitary quest, as it is often the result of collaborative works that are themselves the result of a given social structure. On the social level, the referee system in science involves the systematic use of judges to assess the quality of scientific research. The judges include editors and referees who assess the acceptability of manuscripts submitted for publication, experts who evaluate proposals for research grants, and peers who decide to cite, or not, a piece of work in subsequent publications. Moreover, science is a collaborative process in the making: far gone are the myths of the lonely scientist. Collaboration is increasingly viewed as a necessary step in the production of science. Corroborating this trend, Hicks and Katz (1996) have documented the upward proportion of papers involving collaboration to the detriment of non-collaborative papers. Many empirical findings point at the influence of institutional and contextual factors as important factors determining individual productivity. In a series of works, J. Scott Long and his colleagues (Allison and Long, 1990; Long, 1978; Long and McGinnis, 1981) found that when a scientist is employed in a particular context, his productivity soon conforms to the particularity of this context. The mobility of scientists in prestigious departments increases their rate of publication and citation, while downward mobility to less prestigious departments decreases this rate. Carayol and Matt (2006) found that the intensity and quality of a colleague's research activities within laboratories are beneficial for individual research.

Concerning the propensity to engage in commercial activity, evidence shows that the institution one is in and the attitude of one's colleagues determine partially the rate of engagement with the industry and individual rates of patenting. Group norms regarding industry commitment differ across departmental context. While some researchers regard opportunities arising from technology transfer activities positively, others are more reticent and fear adverse effects on the freedom of research (Lee, 1996). There is evidence that scientists who work closely with commercially inclined peers will be more likely to engage in the commercial transfer of their scientific research. Stuart and Ding (2005) found that faculty members were more likely to become commercially-inclined when they worked in university departments that employed other scientists that had previously ventured into commercial activities. They argue that two mechanisms are at play in the effects of colleague commercial activities on a scientist. First, it legitimates the undertaking by increasing the acceptance of this phenomenon. Second, it lowers the costs of collecting information on commercial sector activities. Bercovitz and Feldman (2008) pinpointed that when the chair of the department is active in technology transfer, other members of the department are also likely to participate. In the same line, Tartari et al. (2010) found that academics' engagement with industry is strongly influenced by their departmental peers' attitudes and behaviors. Individual are at least partially influenced by their localized social environment. All these studies indicate the influence of peers, particularly at the department level.

Hence, we focus our empirical analysis on the department level, as a complementary to the individual level, where scientific collaboration and peer pressure is high. Indeed, the department level is an important element of academic life. Working in a department imposes obligations and responsibilities on academic staff, such as defining teaching programs, sitting on committees, and the like. Hiring and promotion are normally decided at the departmental level. As such, the department generates a web of interaction and overlapping bonds of collegiality. It is a level of analysis where peer pressure is influential and shapes individual behavior. It plays an important role in determining the working behavior patterns and norms of academic life.

In our cross-sectional analysis, we test the influence of departmental colleagues' works on a scientist's propensity to patent. Building on the above references, we hypothesize that a researcher employed in a department inclined to patent will see his/her patenting activity become positively influenced by his/her colleagues' work.

3.3 Financial variables

Crow and Bozeman (1987) underline that the nature of the research (applied vs. basic) is strongly influenced by the funding structure of the laboratory. As such, financial variables are an important input of university research. On top of recurrent funding, a university researcher can seek additional funding through research grants, or work with the industry through joint research, contract research and consulting. Research funding is an important part of academic life: it is certainly a variable affecting the output of a researcher. Having access to additional research funds should therefore enhance outputs. Symmetrically, research funding can also be seen as an indicator of a researcher's capabilities and of the attractiveness of his/her work. Research grants are supposed to be awarded to the most promising projects. And, in the same way, industrial partners try to mate with the most prominent scientists in their field of expertise.

We believe that financial variables should be included in works interested in scientific output, as they convey information on the perceived quality of a research project and the means mobilized to achieve it. This is seldom done in studies focusing on the individual level: this type of data is complicated to obtain. With the exception of the works on University Louis Pasteur in France, (Carayol, 2007; Carayol and Matt, 2006), we are not aware of the inclusion of financial data in this type of research. We expect researchers' patenting and publication performance to increase with the total amount of funds received, and patenting to be positively associated with private funding. We hypothesize that research grants should mainly influence publication outputs and that contractual research should have a positive effect on patenting levels.

3.4 Research questions

The three above-mentioned elements will be used in the following empirical section. First, we will test the relationship between publication and patent, in both number and quality of publication output. We test also their sequential relation in our panel data analysis. From the literature, we hypothesize a positive relation between these two variables in term of quantity. As for quality the empirical results presented in the literature are more thin and we are not sure of the sign of the relation, if any. In terms of peer effects, we hypothesize a relationships between the activity colleagues within a department and an individual propensity to patent. This assumption will be tested in the cross-section experiment. Third, we hypothesize a relation between the patenting and publishing activity and the origin and amount of research funds a researcher receives. In the cross-section analysis, we test the influence of the patenting activity on research grants and contractual money, as well the existence of industrial sponsors. On top of that, in our regressions we control for age and research fields as these variables are likely to influence the outcome (Stephan, 1996), especially since we are interested in seeing whether there are age differences in engaging into patenting. We believe that depending on the age cohort a researcher belongs to, the individual responses to a changing legal environment concerning university technology transfer may differ.

In Section 4, our econometric exercise is centered on a pooled cross-section analysis of 808 permanent academics at the Tohoku University from 2004 to 2007. This analysis starts in 2004, because we were able to access internal document on staff, patents, and research contracts from this date forward. Section 5 is based on a panel data setting of 178 academic inventors who were active in the university from 1994 to 2008.

4 Cross section analysis: Patent and publication activities of Tohoku University researchers

This section attempts to study the determinants of academic patenting using data on a large sample of Tohoku University academic researchers. We examine patenting at the individual level as opposed to the institutional level. Our aim is twofold: (1) to investigate the relationship between patenting and publishing; (2) to examine how patenting activity relates to individual and departmental characteristics. We first explain how we retrieve and organize the data (4.1). This is followed by a description of the sample (4.2). We then move on econometric specifications (4.3 & 4.4), present the results (4.5), and summarize the main findings (4.6).

4.1 Data

Data concerns the research activity at Tohoku University from 2004 to 2007. We decided to start our sample in 2004 as it corresponds to the Incorporation of Tohoku University (See Section 2). From this date onwards, national universities gained more independence and managerial freedom. As a result, we could get access to the documents from the university without needing to ask the permission to the Ministry of Education (MEXT).

We were able to collect comprehensive data on 9 Schools and Institutes: the engineering part of the faculty (Graduate School of Engineering and Graduate School of Environmental Studies[4]), its attached research institutes (Institute for Materials Research, Fluid Science Center, Biomedical Engineering Research Organization, Research Institute of Electrical Communication), and the life and physical sciences related Graduate Schools of the university (Graduate school of Science, Agriculture and Life Sciences). These schools and institutes represent a total of 1,156 permanent academic staffs and a total of 3,693 graduate students. Overall, the university groups 2,681 permanent academic staff and 6,585 graduate students.[5] We did not include in our analysis the humanities and social sciences disciplines, as they are not, in the large majority, involved in the patenting process.

We collect and compile internal documents from three sources: the University Evaluation Center, the Center for Research Strategy and Support (CRESS), and the Human Resource Department. We received a list of all the academic staff on the university's annual payroll from 2004 to 2007 from the human resource department. We excluded from our sample all researchers who were not included in this list so as to ensure that all individuals considered were present over the whole period. 808 scholars remained in our sample. This big drop in the number of researchers finally included in our sample can be explained by the fact that some researchers retired, some of them left the university, and others arrived during the period under study. The documents we collected provided us with a wide range of information about each researcher in our sample. We were able to compile the following individual characteristics on each one of them: sex, age, title, affiliation,[6] and whether they were employed in a teaching and research position or strictly research.

Dependent variable

Our sample represents the lion's share of the scientific research and patenting of the university. Indeed the university is historically strong in the engineering and sciences fields. For the purpose of our analysis, we use the number of patents on which a researcher is listed as an inventor in our

[4]It was established in April 2003, the overall majority of the members came from the School of Engineering.

[5]The figures are for 2007.

[6]By affiliation, we mean which department the researcher belongs.

four-year period as an indicator of patenting activity. We listed the entire patent applications received by the Intellectual Property Office for the period 2004-2007. These are mainly university-owned patents. For each one of these patents, we know who the inventors were, and whether they were part of the university or not. We use these indicators as a proxy to evaluate the involvement of a researcher in patenting activities. Each time an inventor is listed on a patent as an inventor (or applicant) adds to his/her patent count. This is our dependent variable. For simplicity, we refer to it as *Patent*.

Independent variables

To measure publication trends, we rely on two bibliometric indicators: the quantity of the publication output (measured by publication counts), and the quality of the publication output (measured by citations to the journal it was published in). Information on the published articles of each researcher was collected using the Science Citation Index (SCI) databases provided by Thomson Reuters.[7] This database is often used in empirical studies on the subject. For each researcher in our sample, we checked the number of publications referenced in the SCI database for the period 2004-2007. Because of the high frequencies of homonymy in Japanese surnames, when in doubt, we double-checked the results retrieved through the database with internal documents.[8] We have decided to take into account the rough number of publications as we have not tried to correct this number by co-authorship, i.e. papers published with five authors or with two authors are considered to be equal. We refer to this variable as *Paper*. Some studies weigh publications by the number of co-authors, but we feel that this approach is intrinsically flawed. Should the effort of a publication written by three co-authored be divided by three? Does every co-author put the same effort and time in a paper? Does the position in the publication record matter? Do the first and the last authors of a publication carry the same weight in the writing process? With no credible answer to these questions, we argue for the use of a simple count procedure for publications.

In order to account for the quality of a publication, we assign a weight to each one of them corresponding to the impact factor of the journal it was published in. The impact factor of an academic journal is an indicator that reflects the use by the community of the articles published in this journal: the higher the impact, the higher the reputation and diffusion of a journal.[9] This information enabled us to weigh a publication by a measure representing a theoretical impact, and hence to create a performance indicator (*Paper Impact*).

[7]For more information consult: http://www.isiwebofknowledge.com/.

[8]A list of the university researchers' publications is available on http://db.tohoku.ac.jp

[9]For 2007 the impact factor of a journal is calculated as follow: 2007 cites to articles published in 2006-5 divided by the number of articles published in 2006-5.

Control variables

We include in our model a range of control variables. The first group of control variables, as it is common in such studies, relates to the individual features of the academics. We include researchers' academic characteristics such as the academic rank (coded as a dummy variable *Professor*) and the existence of teaching duties (*Teaching*). We also record the age of the researcher *Age*.

On top of that, we control for the amount of research funds received by a researcher. We gathered internal financial data with the help of the Center for Research Strategy and Support (CRESS). We include two types of funds: research grants and contractual funding. For the first one, we incorporate data on Grant-in-Aid for Scientific Research, which is referred to as *Grant*. These grants support research projects submitted on the initiative of the researcher. They cover the full spectrum of scientific research fields from the humanities and social science to natural science. They are an important policy tool of the government to support high level scientific projects. They represent about 37% of total competitive research funding for universities, and therefore are larger than any other programs.[10] Research grants can be applied to one, or several researchers. Our data is limited to the principal investigator, the person in charge of implementing and managing the project, as opposed to the co-investigator who is not given autonomous use of the grant funds. We define the variable Grant as the total amount of research grants a principal investigator received for the project. If the project lasted for several years, we have data on the amount of research funds for every single year. For contractual funding, we create a variable, *Contract*, gathering contractual, commissioned research, and consulting activities. On top of that, we control for the origin of the funds, whether public or private, by generating a dummy variable *Priv.contract*.

A second group of variables are related to each department's characteristics. Our 9 schools and institutes include 65 departments. As discussed in the literature review section (Section 3), we focus on the department level to gauge colleagues' influence on a researcher's work. One possible caveat of such a level of analysis in the Japanese context is that, historically, the chair system, named *kouza*[11] in Japanese, was very strong in Japanese universities. Chair holding professors had near complete authority with regard to decision-making, and the collaboration between chairs in teaching and research was not the rule. For these reasons, departments may not be the best level of analysis. However, over the last decade, the research organization of universities has evolved. It has moved toward a "large" chair system - *Daikoza-sei* in Japanese. The result of this was that an original chair, which consisted of few professors, associates and assistant professors, was amalga-

[10] Numbers for 2002, source MEXT website: www.mext.co.jp

[11] A *kouza* typically consists of one full professor, the laboratory head, one associate professor, and an assistant professor. The system was modeled on the early twentieth-century German university system of professor chair.

mated with other chairs. As noted by Ogawa (2002), the direction of these reforms suggests a move toward a department system common in the US. Therefore, we feel confident to perform our analysis at the department level.

To compute the characteristics of each researcher's colleagues, we take into account all the permanent researchers of a department and exclude the researcher who is analyzed.[12] *Dept.paper* gives the number of publications of departmental colleagues. The variable is corrected for co-publications within a department: if more than two researchers co-authored a publication, it is only counted once. textitDept.patent gives the number of patent of departmental colleagues.The quality of a colleague's publications is proxied by *Dept.Impact*, which corresponds to publication performance of colleagues corrected by impact factor. textitDept.patent gives the number of patent of departmental colleagues, textitDept.grant and . textitDept.contract represent the amount of grant and contract respectively at the department. *Dept.Size* stands for the number of academic staff being employed in a department.[13] Finally, we include dummies for research fields. Unfortunately, for the researchers or even the departments, we could not find precise information characterizing their field of research. We therefore had to find a way to create a discipline dummy variable. To do so, we decided to compile all the publications of each department for our period of inquiry. We based our measure on the fact that each paper is published in a journal that is classified in one of the ten research fields of the SCI database (classification Level 1). For each department, we looked at which field it publishes the most in, and used this category to brand the main field of expertise. We decided to create this variable as it is, in our view, a good way to measure in which field the members of a department were the most active for our period of inquiry.

4.2 Sample description

Summary statistics of the variables are presented in Table 1. Firstly, it is valuable to notice that the average level of publication is overwhelmingly higher than the patent one. The foremost output of an academic researcher is his/her publications. On top of that, as often seen in such studies, the distribution of the variables is very uneven. Both the patent and paper measures appear highly skewed, as shown in Figure 4. The distribution of patents is considerably more skewed, however, than that of publications. Table 2 shows the degree to which patents and publications are related, by examining the joint distribution of patents and article counts. Overall, 102 researchers have no patents or publications in our period of analysis, while 231 have both. These figures account for respectively 13% and 29% of our sample. We see that the large majority of researchers who are the most active patentees are also active in publishing. It is possible to infer from this

[12] We used the complete set of 1,156 academics to compute these variables.

[13] As the number fluctuated over the period for some departments, we record the size in 2007.

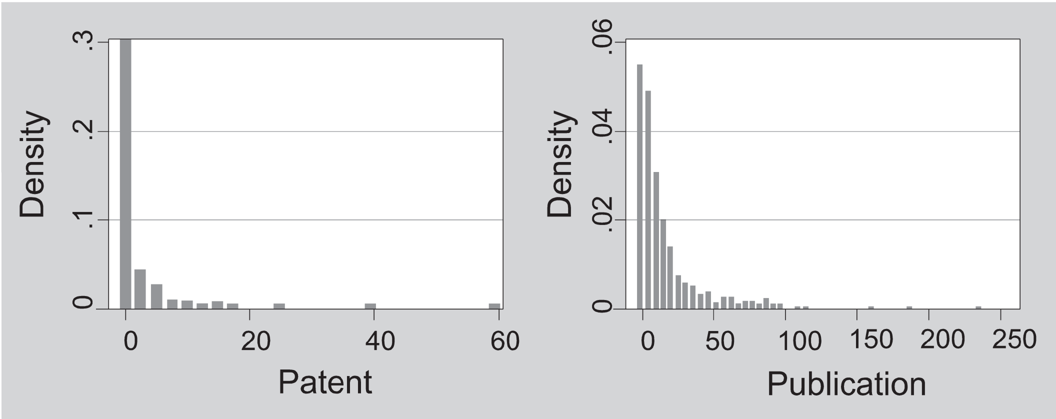

Figure 4: Histogram of patents and publications

Table 1: Descriptive statistics

	Mean	Median	Std. Dev.	Min	Max
Patent	1.28	0	3.65	0	61
Paper	13.21	7	19.68	0	225
Paper Impact	27.91	11.62	49.49	0	601
Grant	289	79	635	0	6822
Contract	153	0	553	0	8813
Ind.Contract	0.28	0	0.45	0	1
Dept.Paper	214	164	178	0	868
Dept.Impact	466	326	480	0	2196
Dept.Patent	15.51	6	23.84	0	104
Dept.Grant	6619	4671	5801	0	23941
Dept.Contract	2920	2846	2377	0	9862
Teaching	0.78	0	0.41	0	1
Prof	0.38	0	0.49	0	1
Age [25-35]	0.19	0	0.39	0	1
Age [36-45]	0.35	0	0.48	0	1

Notes: (1) Monetary accounts are expressed in 1,000$^{\text{th}}$ of dollars, the following exchange rate was used ¥120= $1 evidence that these two activities might go hand in hand, especially among the most prolific and versatile researchers. Further analyses are needed to confirm this conjecture.

Table 2: Patent and publication distribution

	Patent	0	1-5	6-10	1-61	Total
Publication						
0		102	13	2	1	118
1-5		196	42	2	0	240
6-10		96	37	3	5	141
11-225		167	102	29	11	309
Total		561	194	36	17	808

We see also from Table 1 that the average amount of research grants is superior to the average amount of contractual funding. In term of private partnership, 28% of our sample has been engaged, at least once, in a research contract with a corporate partner. As for research fields, engineering and physics account for a bit more than half of the sample.

4.3 Econometric specifications

Our outcome of interest, the number of patents, is a non-negative integer or count. Because the response variable is discrete, its distribution places probability mass at non-negative integer values only. The natural starting point for an analysis of counts is the Poisson distribution and the Poisson model. The univariate Poisson distribution has the following probability mass function:

$$Pr[Y = y] = e^{-\lambda}\lambda^y/y! \quad , \qquad y = 0, 1, 2... \tag{1}$$

where λ is the intensity or rate parameter. The two first moments are:
$E[Y] = \lambda$ and $V[Y] = \lambda$

This shows the well-known equality of mean and variance, also called the equidispersion property of the Poisson distribution. In empirical works, the equidispersion property is often violated, as overdispersion of the data is common. Indeed, overdispersion in count data may be due to unobserved heterogeneity. In that case the conditional variance exceeds the conditional mean. One way to account for overdispersion is to use the negative binomial specification. In such a setting, counts are viewed as being generated by a Poisson process but it is not possible to correctly specify the rate parameter, λ, of the process. Instead, the rate parameter is itself a random variable. If the parameter λ is random, rather than being a completely deterministic function of regressors, then the negative binomial model is used. A way to choose between the two models is to run a formal test of the null hypothesis of equidispersion, $Var(y/x) = E(y/x)$, against the alternative of overdispersion. This test can be can based on the following equation:

$$V(y/x) = E(y/x) + \alpha^2 E(y/x) \tag{2}$$

which is the variance function for the negative binomial model. We test $H0 : \alpha = 0$ against $H1 : \alpha > 1$. We run this test on our data to see whether we are in the presence of overdispersion. The null hypothesis was rejected.

Additionally, our data presents some other particularities that we have to take into account if we want to model our process correctly. Our dependent variable, *Patent*, is heavily skewed to the right, with a high proportion of zero values. Natural candidates for such data are Zero-Inflated Poisson or Zero-Inflated Negative Binomial models (ZIP, ZINB). These models enable us to deal with the fact that the data displays a higher fraction of zeros, or non-occurences, unlike standard count regression models. The zero-inflated model combines a binary variable c with a standard count variable y^* (with support over the nonnegative integers) such that the observed count y is given by:

$$y = \begin{cases} 0 & \text{if } c = 1, \\ y^* & \text{if } c = 0. \end{cases} \tag{3}$$

If the probability that $c = 1$ is denoted by ω, the probability function of y can be written compactly as:

$$F(y) = \omega d + (1 - \omega)g(y) \quad , \qquad y = 1, 2, 3... \tag{4}$$

Where $d = 1 - [\text{min y}, 1]$ and $g(y)$ is a regular count data probability function such as the Poisson or the negative binomial function. The advantage of this formulation is that it can account for two types of zero outcomes. Indeed, zero outcomes can either arise from regime 1 ($c = 1$) or from regime 2 ($c = 0$ and $y^* = 0$).

The question then is whether the characteristic assumption of zero-inflated models, namely two types of zero outcomes, is theoretically appealing or not. In our analysis we are interested in patent applications. It can be argued that a scientist may not be listed on a patent for two reasons: he did not attempt to or he did not have the opportunity. For instance, there are academics that are not interested in applying for a patent, regardless of whether or not some of their research may be patentable. On the other hand, there are academics that are involved in patenting activities, but they may not patent in a given period if the opportunity does not arise. This interpretation sounds quite appealing in explaining different types of zero outcomes, and therefore, we decide to use zero-inflated models.

Following Lambert (1992), we specified a logit model for ω in order to capture the influence of covariates on the probability of extra zeros. For a more in-depth analysis of the treatment of zero in count data models, it is possible to refer to Winkelman (2008) and Cameron and Traverdi (2005). It should to be noted that one of the weakness of our approach in estimating the influence of publications on patents is the potential correlation between publication and unobserved heterogeneity among our scientists. One way to solve this shortcoming would be to use some instrumental variables,[14] but we could not think of any in our setting. Despite this shortcoming, we are confident to have used the appropriate methodology to analyze our data.

4.4 Estimation methodology and test

In this section, we report the result of the different tests that were implemented to justify the models we used for our estimations. First of all, a brief look at the data indicates the presence of overdispersion, indeed our dependent variables have a variance superior to its mean ($Var[yi] \geq E[yi]$). A formal test was conducted to test for overdisperion. The null $H0 : \alpha = 0$ was rejected, it indicates the presence of significant overdispersion. Thus a simple Poisson model would not be appropriate. Such a phenomenon may be due to two non-exclusive phenomena: unobserved individual heterogeneity and/or zero inflation. In fact, together the zero inflated Poisson model (ZIP), the Negative Binomial (NB) model and the ZINB model are natural candidates for us. The ZINB appears to be preferable to the ZIP model which is nested in it, our variables presenting overdispersion.

Table 3: Information criteria

Negative Binomial (NB)			Difference	Prefer
Vs.	BIC	= -3135	dif. = -61.514	NB
Zero Inflated NB	AIC	= 2.386	dif. = 0.058	ZINB
ZINB	Vuong	= 5.179		ZINB

A standard measure to choose between non-nested models is to use information criteria. They are log-likelihood criteria with degrees of freedom adjustment. The model with the smallest information criterion is preferred. The main intuition behind this is that there exists a tension between the model fit, as measured by the maximized log-likelihood value, and the principle of parsimony that favors a simple model. The fit of the model can be improved by increasing model complexity. However, parameters are only added if the resulting improvement in fit sufficiently compensates for loss of parsimony. Two standard measures are Akaike's information criteria (AIC) and Schwarz's Bayesian information criteria (BIC). Smaller AIC and BIC are preferred. It is also possible to test one nonnested likelihood-based model against another using the LR test of Vuong (1989). We have compared NB and ZINB specifications using these three criteria. Results are displayed in Table 3.

The BIC, which penalizes model complexity (the number of parameter

[14]A variable z is called an instrument or instrumental variable for the regressor x in the scalar regression model $y = \beta\, x + u$ if (1) z is uncorrelated with the error u and (2) z is correlated with the regressor x.

estimated) more severely than the AIC, favors the NB model, whereas the AIC favors the ZINB model. The positive value of the Vuong statistic is in favor of the ZINB model. We compared the actual versus the predicted probability of the different events from 1 to 9. Both models were close to actual frequencies.[15] All together ZINB seems to allow a slight improvement over the NB, as shown by the information criteria, but it comes with a price of greater complexity. We will therefore present results for both ZINB and NB models.

Finally, interest often lies in measuring marginal effects, the change in the conditional mean of y when regressors x change by one unit. For the linear regression model, $E[y|x] = x'\beta$ implies $\partial E[y|x]/\partial x = \beta$ so that the coefficient has a direct interpretation as the marginal effect. For nonlinear regression models, this interpretation is no longer possible. For example, if $E[y|x] = exp(x'\beta)$, then $\partial E[y|x]/\partial x = exp(x'\beta)\beta$ is a function of both parameters and regressors, and the size of the marginal effect depends on x in addition to β. In order to have a better interpretation of the coefficient we will present the marginal effects at the mean of the dependent variable (Table 4).

In our estimation we have used robust standard errors in order to adjust for heteroskedasticity in the model and further adjusted them to take into account the clustering implied by the 65 departments.

4.5 Results

Table 5 displays the results. The ZINB models (given in Eq. 3) have two components: the negative binomial part accounts for the numbers of patents invented when individuals are in the patenting regime, whereas the logit zero inflation part explains the switch between the patenting and the non-patenting regimes. Let us note that a positive coefficient in the zero inflation part of the model means a higher chance to remain in the non-patenting regime, which implies zero patent. By using this model, we attempt to capture the difference between scientists who are not involved in patenting because they are not interested, and scientists who are interested but do not necessarily participate in IPR activities during the period under study. The results of the negative binomial specification are provided as well. The marginal effects for the four models computed at the mean of the independent variables are presented in Table 4. Finally, we left out from our analysis 24 individuals belonging to a department specialized in mathematics from our analysis as they did not trigger a single patent during the period of inquiry (in general, pure mathematical concepts are not patentable).

Our first major series of findings tell us more about the effect of publication related variables. We find a positive and significant relation between patenting and publishing in all our model specifications, as hypothesized in

[15] We used the user-written countfit command in STATA to calculate the frequencies.

Table 4: Marginal effects at the mean of the dependent variable

	Model 1a dy/dx		Model 1b dy/dx		Model 2a dy/dx		Model 2b dy/dx		Mean
Paper	0.026	**	0.026		0.017	**	0.030	**	13.52
Paper Impact	-0.003		-0.003		-0.002		-0.005		28.57
Grant	7.02e-05	*	1.21e-05		7.59e-05		2.76e-04		293.19
Contract	3.74e-04		4.85e-04		3.71e-05	*	1.60e-03		157.84
Ind.Contract	1.171	***	0.878	**	0.734	***	0.522		0.28
Dept.Paper					0.004	*	0.006		217.87
Dept.Impact					0.010	**	0.015	**	16.03
Dept.Grant					-2.87e-05		-4.18e-05		6692.62
Dept.Contract					-1.39e-05		1.98e-05		3002.95
Teaching	0.182		0.133		0.133		0.123		0.777
Prof	0.044		0.085		0.152		0.143		0.379
Age [25-35]	1.413	**	1.421		1.014	*	0.680		0.186
Age [36-45]	0.415		0.216		0.375	*	0.025		0.346
Age [46-55]	0.025		0.064		0.089		-0.115		0.268
Physics	-0.597	*	-1.053	**	-0.158		-0.387		0.259
Mat.Science	-0.112		-0.159		0.400		0.994		0.078
Chem.	-0.292		-0.654		0.129		-0.293		0.102
BioChem.	-0.112	***	-0.687		1.004		0.248		0.060
Earth.Science	-0.770		-1.304	***	-0.543	***	-0.951	***	0.055
Biology	-0.368		-0.493		0.082		0.371		0.142
Chem.Eng	-0.013		0.381		0.442		1.405		0.013

Notes: (1) The coefficients of age and discipline variables should be understood in comparison with Age > 55 and Engineering dummy variables which are taken into reference.
(2) Monetary accounts are expressed in 1,000th of dollars, the following exchange rate was used ¥120= $1
(3) * Significant at 5%, ** significant at 1%, *** significant at 0,1%.

our theoretical section. The marginal effects are positive and strongly significant in models 1(a), 2(a) and 2(b). Accordingly, these two activities show recurrent signs of complementarity. Hence, we can confirm in our setting a positive patent-publication relationship as suggested in previous studies. This give weight to the idea that these two types of output are the two sides of the same coin: depending on the nature of scientific results, knowledge flows through one or two channels. If our analysis stopped here, it would be of limited use either practically or theoretically. This is why, when designing our research setting, we have added many control variables, some widely used in the literature, some more idiosyncratic to our rich dataset.

We calculate the influence of publication corrected by its impact. The previous finding does not hold if publications are weighed by the impact factor of the journal they were published in. The variables *Patent* and *Publication impact* are negatively correlated, but this is not significant at the individual level. The story looks a bit different if one considers the quality of the journal in which the articles are published. At the department level, in model 2(a), the number of publications by fellow members of the department are positively correlated to the dependent variable (marginal ef-

Table 5: Results of the regressions with Patent as the dependent variable

Dependent variable	Patent		Patent				Patent		Patent			
	Model Neg Bin	1(a)	Model ZINB	1(b)			Model Neg Bin	2(a)	Model ZINB	2(b)		
			Neg Bin		Logit				Neg Bin		Logit	
Paper	0.035	**	0.021	*	-0.287		0.028	**	0.021	*	-0.028	
	(0.012)		(0.009)		(0.681)		(0.011)		(0.009)		(0.030)	
Paper Impact	-0.004		-0.003		0.068		-0.003		-0.005		-0.004	
	(0.004)		(0.004)		(0.2)		(0.005)		(0.004)		(0.014)	
Grant	9.88e-04		-2.94e-06		-4.77e-03		1.26e-04		-1.10e-05		0.002	*
	(9.18e-04)		(8.77e-05)		(1.46e-02)		(8.59e-05)		(8.97e-05)		(0.001)	
Contract	5.27e-04	*	3.53e-04	**	-2.29e-02		5.72e-04	*	3.28e-04	**	-0.006	
	(2.28e-04)		(1.22e-04)		(4.48e-02)		(2.37e-04)		(1.12e-04)		(0.005)	
Ind.Contract	1.199	***	0.641		-1.822		0.906	***	0.108		-2.279	**
	(0.218)		(0.580)		(2.945)		(0.202)		(0.210)		(0.712)	
Dept.Paper							0.010	**	0.005		-0.015	*
							(0.003)		(0.004)		(0.008)	
Dept.Impact							-0.004	**	-0.002		0.007	*
							(0.001)		(0.002)		(0.003)	
Dept.Patent							0.013	**	0.010	*	-0.012	
							(0.005)		(0.005)		(0.009)	
Dept.Grant							-2.54e-06		-1.88e-05		6.69e-05	
							(3.59e-05)		(3.42e-05)		(9.60e-05)	
Dept.Contract							-2.81e-05		5.04e-05		1.76e-05	
							(4.56e-05)		(6.66e-05)		(1.64e-04)	
Dept.Size							-0.019		-0.011		0.023	
							(0.011)		(0.008)		(0.025)	
Teaching	0.274		0.116		-0.548		0.201		-0.048		-0.796	
	(0.189)		(0.253)		(1.167)		(0.186)		(0.161)		(0.429)	
Prof	0.061		0.078		1.543		0.352		0.316		0.756	
	(0.312)		(0.323)		(3.598)		(0.286)		(0.266)		(0.591)	
Age [25-35]	1.256	***	0.891	*	-0.068		1.143	***	0.189		-1.847*	
	(0.338)		(0.450)		(1.962)		(0.325)		(0.354)		(0.875)	
Age [36-45]	0.531		0.181		0.329		0.610	*	-0.084		-1.366	
	(0.271)		(0.279)		(2.245)		(0.274)		(0.276)		(0.803)	
Age [46-55]	0.034		0.069		2.402		0.298		-0.025		-0.273	
	(0.244)		(0.292)		(5.804)		(0.232)		(0.255)		(0.876)	
Physics	-1.031	*	-1.124	**	-0.578		-0.446		-0.547		-0.693	
	(0.415)		(0.429)		(3.522)		(0.269)		(0.300)		(0.744)	
Mat.Science	-0.169		-0.144		0.042		0.472		0.677	*	0.343	
	(0.413)		(0.433)		(2.291)		(0.326)		(0.264)		(0.884)	
Chem.	-0.494		-0.736		-0.383		0.262		-0.349		-1.417*	*
	(0.526)		(0.544)		(0.659)		(0.303)		(0.343)		(0.617)	
BioChem.	-0.169		-0.832		-13.721		1.008*	*	-0.106		-15.113	
	(0.435)		(0.534)		(7.431)		(0.466)		(0.508)		(11.022)	
Earth.Science	-2.729	***	-2.990		-1.553		-1.900	***	-1.257	***	1.315	
	(0.464)		(3.398)		(24.018)		(0.505)		(0.370)		(1.017)	
Biology	-0.639		-0.498		0.898		0.128		0.362		0.459	
	(0.595)		(0.726)		(2.304)		(0.496)		(0.367)		(0.801)	
Chem.Eng	-0.017		0.297		1.822		0.357		0.787	**	0.936	
	(0.363)		(0.383)		(2.754)		(0.324)		(0.385)		(0.869)	
Constant	-1.225	*	0.000		1.636		-1.801	***	0.015		2.749	*
	(0.616)		(1.024)		(1.409)		(0.516)		(0.481)		(1.268)	
alpha	2.880	***	1.781	***			2.411	***	1.198	***		
	(0.489)		(0.634)				(0.324)		(0.229)			
Log pseudo-likelihood	-962.896		-918.113				-931.331		-887.351			

Notes: (1) The coefficients of age and discipline variables should be understood in comparison with Age > 55 and Engineering dummy variables which are taken into reference.
(2) Monetary accounts are expressed in 1000^{th} of dollars, the following exchange rate was used ¥120= $1
(3) * Significant at 5%, ** significant at 1%, *** significant at 0,1%.

fects go pairwise), whereas colleagues' publications corrected by impact are negatively correlated with patenting. Moreover, in the specification 2(b), the publication impact coefficient of the zero-inflated part is positive and significant. Therefore, the quality of the department publications affects the probability of a researcher to stay in the non-patenting regime. We can see in this tendency a kind of specialization, with some departments putting more focus on publishing in high quality journals and some others conducting research related more to patenting outcomes. This result gives credence to our hypothesis that research is a collaborative process. Taking place at the departmental level, a scientist research endeavor being woven to the work of his immediate colleagues. A peer effect is clearly emerging. This will be confirmed by other variables.

On a more direct relation, the level of colleagues' patents positively affects a researcher's propensity to patent: coefficients are positive and significative under negative binomial and ZINB specifications. Marginal effects are positive and significant. Patenting and working with the industry are skills that differ from the traditional research repertoire (Owen-Smith and Powell, 2001). Applying for a patent is a lengthy and complicated process. Learning from colleagues how to decipher the arcane of application procedures can facilitate and encourage individuals to engage in such an activity. On top of that, colleague's patentable research projects can plant the seeds for one's own research projects. Once again, we see the influence of a platoon of sharp colleagues active in a field of expertise.

Let us now focus on the financial characteristics. The amount of research contracts that a scientist manages has a positive and significant impact on all models. As for the dummy for funds originating from industrial partners, it is positive in models 1(a) and 2(a), and is negative in the logit part of model 2(b). The marginal effects support these results. The magnitude of the coefficients is quite large as well. The Binomial coefficient on *Priv.Contract* implies that, other factors being equal, the expected number of patents for a research having at least an industrial contract is about two times higher than for the other scientists. Moreover, getting contractual funding from the industry positively affects the probability to reach the patenting regime. Results from University Louis Pasteur in France reveal similar trends. Carayol (2007) found that laboratory contractual funding, and the share of it coming from private sources, increases the probability to patent. In our framework, colleagues' contracts do not affect a researcher's propensity to patent. This difference may be due to the difference in the data: they collected data on the laboratory level, whereas we had access to individual level data. The amount of research grants is only significant in the inflated part of model 2(b). Having more research grants influences the propensity to stay in the non-patenting regime. From these results, we see a clear influence of financial variables and a clear distinction between the effect of research grants and research contracts. The former has no visible influence on the propensity to patent. At the least, it encourages researchers to stay in the non-patenting regime. The latter has a positive impact on the patenting activity, to an even greater extent if the funds come from private partners. The question, then, is whether contractual funding goes to professors who are active in application-oriented research or if faculty members have engaged in marketable research to shore their works with additional funds.

Concerning the control variables, neither the dummy variable controlling for teaching activities nor the one accounting for the academic rank, *Professor*, affect the dependent variable. The *Age [25-35]* dummy variable, the youngest group, correlates positively with patenting in three out of four of our regressions. Marginal effects are positive for this group. We test this result with some other specifications. We made age groups of equal proportions, each group having the same number of people. The results are similar. The youngest group is more active in comparison to the older one. We tried, as well, using the age as the control variable, the coefficients are negatives in models 1(a&b) and 2(b).[16] The results do not confirm the belief that patent productivity increases over the lifetime (Ledebur, 2009). These results contrast with the ones from the University Louis Pasteur (Carayol, 2007) and a sample of American life scientists (Azoulay, 2006). One explanation to these results lies in the fact that the changes of university policy were quite new: the younger researchers might be more prone to integrate patents in their research practices. Lastly, the dummy variable for discipline unveils important differences among specialties. In comparison to the engineering disciplines, physics and earth sciences depict negative tendencies.

4.6 Summary of the main findings

This analysis has brought three clear-cut results. First, we found a positive relation between the number of patents and publications a researcher produces. However, when we take into account the impact of the publication, no correlation appears. This suggests that productive researchers can combine both activities. Quality of publication does not seem to have an influence on the patenting output. We also showed that the origin and amount of research funds that are managed by faculty members has an influence on the patenting output. Traditional research grants do not seem to influence the patenting activity. However, research contracts, which are more directed towards applications by definition, have an effect on patenting activity, as well as on the type of partners of these contracts. Having worked with an industrial partner influences positively the patenting output.

Second, there is convincing evidence for the existence of a peer effect. The output of colleagues working in the same department influences one's propensity to patent. The number of colleagues' publications positively affects a research patenting level as well as their patenting activity, while the quality of their publications has a negative impact. From these results, we

[16] We do not report the results in the text. Results can be provided on request.

can argue that the type and quantity of a researcher's colleagues influence his own productivity and type of research.

Third, we found that the younger cohort of researchers were more actively engaged in patenting activity than their older peers, reflecting a better adaptation to the new legal environment more prone to technology transfer activities as a core mission of an academic researcher. In the next section, we run regressions on a panel of university scientists which will generate complementary information to these results.

5 A panel data analysis: The case of a group of early patent adopters

This section aims at completing the previous one by using a panel data framework. Using panel data instead of cross-sectional data enables us to enrich our analysis by introducing a time dimension and to control for individual heterogeneity. Our data consists of a 15-year sample of academic scientists from Tohoku University. One difficulty encountered in our analysis was collecting data on patenting for such a relatively extended period. Indeed, as we have demonstrated in the first part of this paper, before the Japanese Bayh-Dole Act and Incorporation of national universities, university-owned inventions occurred very rarely. In order to circumvent this issue of measurement, we used invention disclosure reports of the pre-incorporation period to monitor researchers active in IP activities before 2004. This enabled us to constitute a panel of 178 scientists from 1994 to 2008.

In this section, we question to what extent and in which direction faculty patenting affects the rate of production of scientific output. We first explain how we retrieved and organized the data (5.1). This is followed by a description of the sample (5.2). We, then, present the main results (5.3), and conclude with a summary of the main findings (5.4).

5.1 Data

The empirical analysis relies on a sample of university scientists who have patented at least one of their research results. One of the major difficulties of our endeavor was to collect data on patenting, as the majority of academic patents before 2004 were invented by university researchers, but applied for by corporate partners. University-invented patents, unlike university-owned patents, are notoriously difficult to identify in patent databases. For several European countries, the KEINS project mitigated the problem by collecting and using government listings of university researchers to search patent documents (Lissoni et al., 2007). Unfortunately, we do not have knowledge of such documents for the Japanese context. However, we use data from Kanama and Okuwada (2007) who conducted research on patenting at Tohoku university. Despite the very low level of university-owned patents before 2004, they attempted to verify whether or not some university-invented patents were filed before this date. They obtained data from the university on all the researchers who reported at least one invention disclosure during the 1993-2004 period. In doing so, they were able to spot who was active in technology transfer activities. They recorded 348 individuals who reported at least one invention disclosure. Using the names of these individuals, they searched the Japanese Patent Database in the inventor section for patents applied from 1993 to 2004.[17]

We built upon this database. First, we restricted the sample to the faculty who were still on Tohoku University payroll in 2008. We were left with 264 individuals. Then, using various Internet searches,[18] we restricted our sample to the scientists who were in the university in 1994. None of the researchers who had reported an invention disclosure in 1993 were still in the university in 2008. Finally, we found 178 individuals who were in the university from 1994 to 2008.

We used the data from Kanama and Okuwada (2007) for the 1994-2004 period. We just recoded the years as we switched from publication year to application year. We preferred to use the application year, as it is closer to the actual research and free from legal considerations that might make the time elapsing from application to publication among patents vary. We thereafter performed a manual search on these researchers for the years 2005 to 2008. We complemented this data with internal documents for the more recent patent applications, as some of them, especially for 2008, might not be publicly available yet.

As in the previous sections, information on the published articles of each researcher was collected using the Science Citation Index (SCI) databases provided by Thomson Reuters.[19] For each researcher of our sample, we checked the number of publications referenced in SCI for the period 1994-2008. Because of the high frequencies of homonymy in Japanese surnames, we have double-checked our results with internal documents.[20] For control variables, we included research grants. As we could not have information from the university before 2004 on this variable, we retrieved them from the Grant-in Aid for Scientific research Internet database.[21]. As in the previous section (4), we limited our retrieval of data to the case where the researcher was the principal investigator. In that case, he has the charge to implement and manage the project, as opposed to the co-investigators who are not given autonomous use of the grant funds.[22] We define the variable *Grant*

[17]Search was performed using the Intellectual Property Digital Library (IPDL) from the Japanese Patent Office.

[18]We searched for curricula, affiliation in publications, and research grants documents to accomplish this task.

[19]For more information consult http://www.isiwebofknowledge.com

[20]A list of the university researchers' publications is available on http://db.tohoku.ac.jp

[21]http://kaken.nii.ac.jp

[22]Our choice is supported by the research reports published at the end of the grants: number of publications, attendance to conferences, etc.). Theses reports show the central

as the total amount of research grants received for a project. In the case of a project spanning for several years, we include data on annual research funding. The maximum time frame for grants labeled "scientific research projects on priority areas" is 6 years. Finally, we count the number of research grants a scientist had in a given year to account for the dynamic of researcher works: the more projects being run in a given period, the wider the potential opportunities. We labeled this variable *Grant Count.*

In order to control for the effect of age in the publication and patenting activities, we include the Age variable of the researcher in our analysis. Finally, we checked if our researchers were promoted during the 1994-2008 period, and created a dummy variable, *Promotion*, that takes the value one if promotion occurred in our timeframe.

5.2 Sample description

Table 6: Descriptive statistics

-	Observation	Mean	Std. Dev.	Min.	Max.
Patent	2655	1.21	2.49	0	27
Paper	2655	6.77	6.81	0	88
Grant	2655	3.15	6.62	0	125.97
Grant Count	2655	1.04	0.98	0	6
Promotion	2655	0.05	0.23	0	1
Age	2655	44.46	8.17	25	65

Table 6 provides summary statistics for the variables used in the analysis. Figure 5 displays patenting and publishing rates over time. Three elements are worth commenting on. First, publishing is a much more important activity than patenting – this is similar to what was found for MIT by Agrawal and Henderson (2002). Second, both publishing and patenting rates increase significantly over the period. The patenting rate increases steadily until it reaches a plateau in 2003. The publication rate increases steadily the first few years as well. This trend can certainly be explained by fact that few faculty in our sample started their academic career in the first year. Their productivity increased over time along with career opportunities.

Third, in comparison to other studies of similar scope (Agrawal and Henderson, 2002; Czarnitzki, et al., 2009; Fabrizio and Di Minin, 2008; Goldfarb and Marschke, 2006) our sample exhibits a very high average number of publications and patents. For patents, they are above any study we are aware of. This reveals one of the major benefits, and drawbacks, of this study: we are in presence of a very high technologically inclined sample of individuals. It is therefore very interesting to analyze the behavior of such a population,

role of the principal investigator. Indeed, we examined the research reports of our most prolific scientists. We noticed that the principal investigator was nearly always included in them.

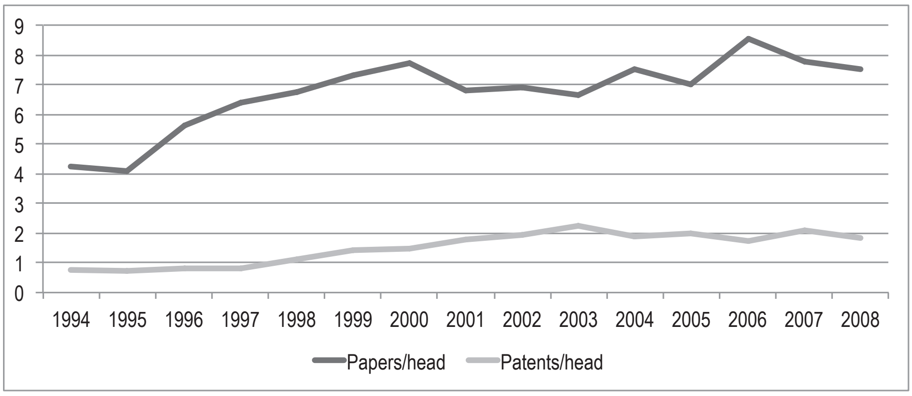

Figure 5: Papers and patents per faculty

as they might combine academic and technological parts of their work. The problem with this is that results might not be easily generalized.

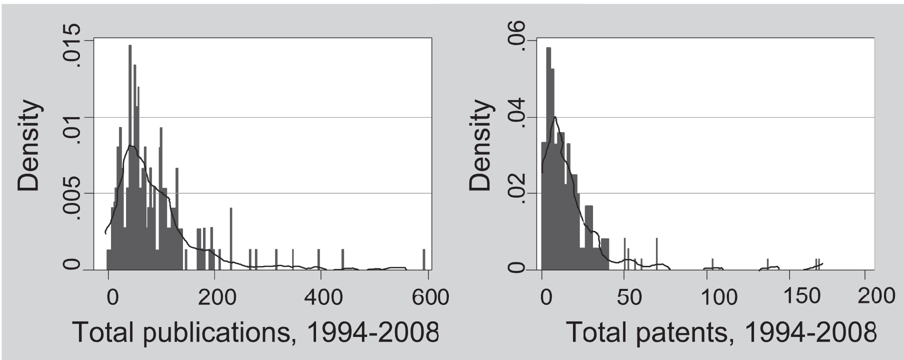

Figure 6: Publication and patent frequency

Figures 6 presents a histogram of the total number of both patents and publications. Both distributions are heavily skewed to the left, even though for publication data the histogram is more flat. These results are in line with general results of scientific productivity: very few scientists are producing the bulk of the writings, while a silent majority uncloaks very low levels of outputs. Table 7 shows correlation coefficients of flow measures for patenting and publications. There is a clear correlation between patenting and publication over time. The table gives evidences that patenting and publishing behaviors are correlated with each other, with all the correlation coefficients in the range of 0.16 to 0.18.

5.3 Empirical analysis and results

To investigate the patent-paper relationship we employ fixed-effects Poisson models as introduced by Hausman et al. (1984). As the basic Poisson model assumes equidispersion, i.e. the equality of the conditional mean and

Table 7: Correlation matrix

	Paper	Paper (t-1)	Paper t-2)	Paper (t-3)	Patent	Patent (t-1)	Patent (t-2)	Patent (t-3)
Paper	1.0000							
Paper(t-1)	0.7597	1.0000						
Paper(t-2)	0.7016	0.7607	1.0000					
Paper(t-3)	0.6278	0.6994	0.7609	1.0000				
Patent	0.1767	0.1618	0.1615	0.1774	1.0000			
Patent(t-1)	0.1862	0.1727	0.1650	0.1663	0.8689	1.0000		
Patent(t-2)	0.1706	0.1799	0.1657	0.1617	0.8519	0.8704	1.0000	
Patent(t-3)	0.1692	0.1652	0.1738	0.1663	0.8231	0.8552	0.8702	1.0000

the variance, scholars have used negative binomial regression models in the past decades, as these allow for overdispersion, which is typically present in microdata. Overdispersion refers to the fact that the variance is larger than the conditional mean. However, Wooldridge (1999) has shown that the Poisson model is consistent in spite of over-dispersion. In that case, standard errors are biased and thus have to be corrected, which amounts to the calculation of fully robust standard errors.

We employed the following model with publications as the dependent variable, incorporating unobserved heterogeneity through a fixed-effect model. Our specification looks as follows:

$$E(y_{it}|x_{it}, \alpha_i) = \alpha_i exp(x'_{it}\beta) \quad (5)$$

where α_i denotes the individual-specific effect. The α_i are random variables that capture unobserved heterogeneity. The key assumption here is that the unobservable α_i are time-invariant, rather than being of a more general form α_{it}. This denotes the unobserved ability of a researcher that might be caused by factors such as better education, creativity, intelligence, higher ambition or even luck. The use of fixed effects specifications is often favored in studies using microeconomic data. However this comes at a cost: time-constant variables cannot be included in a fixed-effects model. As a result, individual specific attributes of the researchers, such as status, gender and field of expertise, cannot be included. In order to test the rightfulness of the fixed effects specification we have run a series of Hausman tests of random versus fixed effects. They reject the random effects model in favor of the fixed effects model.

We estimate Equation 5 using a conditional fixed effects Poisson quasi-maximum likelihood estimation. This functional form is quite flexible, allowing for correlation in the variance co-variance matrix to adjust the standard errors to the possibility of correlation across observation a given individual. Gourieroux et al. (1984) have shown that because the Poisson model is in the linear exponential class, its coefficient estimates are consistent if the mean is correctly specified (the robust standard errors are consistent even under misspecification of the distribution). We therefore report robust standard errors. However, it is possible to improve efficiency by making more restrictive assumptions on the way the variance differs from the mean, which is why we also report results of negative binomial regressions.[23]

We have decided to address the endogeneity problem common to such analyses by using fixed effect model. Another method would have been to consider patenting as a treatment effect (Frabrizio and Di Minin, 2008; Azoulay et al., 2006 ; Buensdorf, 2009). In that way it is possible to test whether the advantage of academic inventors (the treated group) over their colleagues (the control group) increases after applying for a patent. Despite of the advantage of such a treatment, we were not able to implement it, as we could not create a control group of researchers, due to the fact that we could not retrieve patent data without an address for all the period.

The results show that patenting and publication are related (Table 8). In specification 1(a&b) and 2(a&b), we regress a count of patent on a count of paper. The coefficients are positive and significant in the Poisson regression 1(a&b) and in the negative binomial regression with lagged values 2(b). While the lagged variable $paper_{(t-3)}$ positively influences patent output in both specifications, it is significant in only the Poisson model. This provides an argument to the idea that patents and papers are two channels used simultaneously to communicate the results of an ongoing research agenda. Patents are most often the by-product of a fertile research project.

We ran regressions including the *grants* and their lagged values, but none of the relative coefficient was of any statistical significance.[24] We therefore used the number of grants that a scientist was managing in a given year (*Grant Count*) . The intuition behind this was that the important factor might not be the amount of money received, but rather the number of opportunities that multiple projects could generate. The results confirm this intuition: the number of grants in year (t) have a positive impact on the dependent variable on models 1 and 2. The number of grants in year (t-2) is slightly significant (at the 10 percent level) in both model. The dummy variable, *promotion*, is positive in both models, but only significant in the Poisson model. People who have been promoted patent more than the one's who have not. Being promoted gives more freedom to an academic to pursue his or her research, and therefore could lead to more patenting activities. In parallel, patents increase at a decreasing rate with age. This result is in contrast with the one we found for the cross-section analysis. The reason for this may lie in the timeframe difference. In the cross-section, we focus on a post-reform sample, where many young researchers have started to patent, responding to policy incentives toward a pro-IP attitude, therefore biasing results in favor of the younger cohort. In the panel setting, we have a sample of experimented researchers who have all patented their discoveries at least

[23] All regressions using the conditional fixed effects Poisson quasi-maximum likelihood estimation were performed in STATA using the user-command *xtpqml* written by Tim Simcoe.

[24] In order to not overwhelm the manuscript we do not report the results, they are, however, available on request.

Table 8: Fixed Effect Regressions' Results

	QMLE Poisson Patent 1(a)	QMLE Poisson Patent 1(b)	NegBin Patent 2(a)	NgBin Patent 2(b)	Logit Patent Event 3(a)	Logit Patent Event 3(b)
Paper	0.0185^{***}	0.0162^{+}	0.0100	0.0148^{+}	0.0368^{+}	0.0339^{+}
	(0.00517)	(0.00566)	(0.00678)	(0.00586)	(0.0113)	(0.0123)
Grant Count	0.0973^{+}	0.0748^{+}	0.0825^{+}	0.0878^{+}	0.0290	0.0136
	(0.0333)	(0.0367)	(0.0379)	(0.0393)	(0.0624)	(0.0688)
Promotion	0.146^{+}	0.159^{+}	0.157	0.168	0.238^{+}	0.231^{+}
	(0.0830)	(0.0829)	(0.125)	(0.124)	(0.138)	(0.139)
Age	0.335^{***}	0.321^{***}	0.352^{***}	0.322^{***}	0.574^{***}	0.577^{***}
	(0.0434)	(0.0441)	(0.0705)	(0.0747)	(0.0790)	(0.0795)
Age^2	-0.00289^{***}	-0.00276^{***}	-0.00298^{***}	-0.00265^{***}	-0.00497^{***}	-0.00502^{***}
	(0.000460)	(0.000468)	(0.000697)	(0.000738)	(0.000850)	(0.000855)
Paper(t-1)		0.00587		-0.00387		0.0195
		(0.00575)		(0.00502)		(0.0119)
Paper(t-2)		-0.00515		-0.00589		-0.00894
		(0.00613)		(0.00374)		(0.0120)
Paper(t-3)		0.0114^{+}		0.00629		0.0269^{+}
		(0.00558)		(0.00456)		(0.0108)
Grant Count(t-1)		0.0348		0.00958		0.0334
		(0.0396)		(0.0350)		(0.0729)
Grant Count(t-2)		0.0741^{+}		0.0627^{+}		0.0572
		(0.0383)		(0.0257)		(0.0730)
Grant Count(t-3)		0.0356		0.0102		-0.0272
		(0.0351)		(0.0339)		(0.0662)
Constant	-9.161^{***}	-9.009^{***}				
	(0.998)	(1.010)				
N	2655	2652	2655	2652	2580	2577
Log lik.	-2667.9	-2652.9	-3008.9	-2994.3	-1074.8	-1067.6

Notes: (1) Patent event is a dummy variable taking the value 1 if at least one patent was applied by a researcher for in a given year.
(2) Robust Standard errors in parentheses for the QMLE models
(3) $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

once: their decision to do so preceded policy changes. In that regard, the decision to patent increases with age, as it has been found in other studies. Older scientists have more opportunities and are freer from academic career criteria to engage in IP activities.

Finally, we estimate the determinant of faculty patenting behavior. We create a dummy variable, *Patent event*, taking the value one if a researcher invented at least one patent for a given year, and zero otherwise. In doing so, we estimate what influences a scientist's propensity to patent. We do so by estimating a fixed-effect logit model. By using the variable Patent event, we treat patenting as a repeatable event. The results presented in Table 8 (Model 3) show that the number of $paper_{(t)}$ and the number of $paper_{(t-3)}$ increase the probability to encounter a patenting event in a given year. The dummy variable, *promotion*, is positive and significant in model 3(a & b).The Grant variables do not seem to influence the probability to patent.

5.4 Summary of the main findings

The main added-value of this section, in comparison to the cross-section one, is to have introduced a dynamic of temporality. We found simultaneity in the publication of research results through patent and publication. Patent applied in *time t* are correlated to paper published in *time (t).* This supports the idea that patent and papers are two channels used simultaneously to communicate the results of an ongoing research agenda (Murray, 2007). Additionally, papers published in *time t-3* positively influenced the patenting activity in *time t*, indicating the influence of past research projects in the production of patentable research results.

Finally, the number of publications and patents per year increases with the age of the scientist, but at a decreasing rate over time. Researchers who have been promoted during our period of inquiry have a higher patenting activity than their non-promoted peers. In terms of opportunities, we have shown that the number of research grants a scientist manages, and not the amount of these grants, is positively linked to the patent application level.

6 Conclusion

We started this paper by explaining the policy changes that took place in Japan regarding university-industry relations, especially focusing on IP rights. We then moved to two econometrics exercises centered on the case of Tohoku University. First, we have documented the policy-push directed toward an intensification of university-industry relationships that occurred recently. As a result, the number of academic patents have increased rapidly. However, this increase did not originate from scratch. Particularly, before the Incorporation of national universities the majority of IP rights were transferred informally to industrial partners, this practice has changed nowadays as universities are managing a larger share of the IPs originating within their walls. This increasing use of formal IP rights made vivid the needs for an answer to the following question: What factors influence patenting activities within academia: scientific productivity, funding, colleagues, individual characteristics? The answer to this question was at the core of our econometric exercises. This leads us to our second set of results, these findings can be summarized in three points.

First, we found that patenting and publishing were complementary in our two empirical settings, first, within a large dataset comprising the majority of the faculty members of the engineering and science departments, and second, in a smaller sample of commercially-inclined scientists. Additionally, we found evidence of a peer effect in the patenting production process. The output of colleagues working in the same department influences a researcher propensity to patent. Not only the level of colleagues' patents has a positive effect, but as well the number of their publications positively affects a researcher patenting level, while the quality of their publications has a negative impact. From these results, we can argue that the type and quantity of outputs of a researcher's colleagues influence his/her own productivity and type of research.

Another interesting result concerns the influence of a researcher's age on his/her propensity to patent. In our panel data framework, as one would expect from results in similar studies, the number of patent per year increases with the researcher's age, but at a decreasing rate over time. Contrastingly, in our snapshot of the post Incorporation era, the tendency is reversed, the youngest cohort of researchers, between 25 and 35 years old, is the most active in patenting their results. This may indicate the influence of policy changes: the younger researchers are more prone to embrace patenting as one element of their daily research, because their social environment publicizes the activity as a routine activity that is part of their duties.

A third accomplishment of this paper is highlighting the importance and influences of contractual funding and research grants on patenting and publishing. The results show that contractual research and patenting go hand-in-hand. The amount of contractual funds received by a researcher is positively correlated with his/her number of patents. Having worked with an industrial partner increases a researcher's propensity to patent. As for funds received from research grants, they are not correlated with the level of patenting. Nevertheless, we did find a positive relation between the number of grants – not the amount – a scientist manages in a given year and his patenting output. Our educated guess on the matter is that research grants are mainly channeled toward traditional goals of academic research, the main desirable outcome being publications. This process is self-reinforcing: the more publications you have, the more people are willing to provide you funding. This phenomenon is known as the famous Matthew effect. Furthermore, if a scientist is engaged in many research trails, commercial opportunities are more prone to appear, as the potential commercial uses of scientific discoveries multiply. Our results give supporting evidence to this idea.

The results in this paper have demonstrated the need to consider the financial aspect of the picture. In our view, this element has to be included in any further study, when available. The use of patent documents and their citations, as well as the use of publications, their citations and relative impacts provide some valuable information on the output side of the story. More and more refined techniques are used to take advantage of this data. For instance, Rosell and Agrawal (2009) compared university-to-firm patent citations across two time periods to show that the university diffusion premium – the fact that university knowledge is more widely distributed than knowledge of firms – declined in recent years. Despite these useful refinements, we believe that there is a need to enrich the input side of the story to study how different sources of funding shape the rate and direction of innovative activity.

From this paper's findings, we begin to realize that university-industry relationships and the norms and practices attached to it are influencing the way university scientists do research. University and industry practices are becoming more alike. We can here mention the idea of isomorphism. In the 1990's, Hackett (1990) developed this idea when arguing that changes in external relations of universities would affect their internal practices in the future. Greater dependence on the private sector for resources could lead universities to increasingly resemble the private sector. To the least, we could talk of complementarities, as noticed by an engineering faculty member interviewed by Agrawal and Henderson (2002, p. 58) who stated that "most patentable research is also publishable." One reason for this duality is the high prevalence of research that is both use-oriented and also oriented towards fundamental understanding – what Donald Stokes calls Pasteur's Quadrant. Empirically, Fiona Murray and her collaborators in a series of works on biotechnology related fields found that many research results are both patented and published (Murray, 2002; Murray and Stern, 2007; Murray and Stern, 2008). This concept of co-occurence of research is calling for further research.

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