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Creative Destruction in the Era of Open Innovation:
Empirical investigation into the relationship between patenting and survival of Japanese firms*

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Abstract

This paper uses patent filings as an indicator of innovation and investigates the relationship between innovation and the survival of young firms, based on a dataset linking the Economic Census and the Institute of Intellectual Property (IIP) Patent Database for Japanese firms. We construct indicators showing the organization of innovative activities, such as external collaboration on inventions and the type of collaborative partners, and disentangle two competing factors on innovative activities, i.e., technological capability (positive influencing firm survival) and commercial risk (negative influencing firm survival). We find that positive impacts surpass negative ones in general, and this tendency strengthens when patents have relatively greater potential market value. In addition, collaboration with universities invariably leads to a higher probability of survival, while the impact of collaboration with other firms depends on firm size, namely, a certain level of managerial resources to overcome the complexity involved in open innovation is required to achieve gains from collaboration.

Keywords: Industrial dynamics, Patent, Collaboration, Firm survival

JEL classification: L25, O13

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1. Introduction

Productivity increase is an important factor for economic growth in developed nations. It has been found that 20%-40% of productivity in the OECD countries is attributable to new high-growth startups (OECD, 2003). The importance of entrepreneurship for economic growth is stressed by Schumpeter, who defines “innovation” as the new combination of five types of activities, including new product development and new process adaption (Schumpeter, 1934). Schumpeter also argues that “creative destruction” is an essential element of capitalism (Schumpeter, 1942). The concept of creative destruction, in which firms that successfully innovate increase market share while firms whose productivity is low withdraw from the market, has made a significant contribution to discussions about economic expansion for long time (Baumol, 2010).

Along this line, the view that small and medium-sized enterprises (SMEs) are a source of innovation is shared in every country around the world. However, empirical research on firm dynamics and its contribution to economic development shows mixed results. First, research has found that the survival rate of new firms is low. According to Bartelsman et al. (2005), in a study of 10 OECD countries, 20%-40% of new companies disappear within two years after establishment. Furthermore, it is also understood that there is a positive correlation between entry and exit of firms that occurs in conjunction with macroeconomic fluctuations (Bartelsman et al., 2005). As a result of the churning effect resulting from market fluctuations, generation and dissolution of small inefficient firms that have not reached a sufficient scale occurs simultaneously. This phenomenon can be viewed as firms simply moving through a revolving door (Santarelli and Vivarelli, 2010).

A theoretical model of firm exit or survival is based on new and existing players in the market, taking into account heterogeneous firm capabilities. A passive learning model explains the industrial dynamics of the process through which a firm learns its own initially endowed capabilities, which it was not aware of at the time of entry (Jovanovic, 1982). By contrast, there is also an active learning model which holds that firm capability is not only determined by its initial endowment, but also subsequent investments (Ericson and Pakes, 1995). In both models, young firms are more likely to exit the market, but they suggest that firm technological capability is an important predictor of survival and growth.

Empirically, a large number of studies point to a positive relationship between a firm’s survival and its innovation and patents. Different studies have posited a variety of indicators reflecting innovation, such as R&D expenditures (Esterve-Perez and Manez-Castillejo, 2008), patents (Cockburn and Wager, 2007; Helmers and Rogers,

2010) and successful innovation output as collected in Community Innovation Survey data (Cefis and Marsili, 2005; Cefis and Marsili, 2006), but all of these studies show a positive impact from innovation on survival. However, recent studies have revealed that this positive relationship is context based, and this relationship turns into negative in some cases (Hyytinen et al., 2015). For example Buddlemeyer et al. (2010) shows that patent stock (a reflection of technological capability) is positively related to firm survival, but patent application has a negative influence due to the higher risks associated with new technology development. Boyer and Blazy (2014) also show a negative relationship, particularly for young firms, since market application challenges presented by new technology are riskier for young inexperienced firms. Hyytinen et al. (2015) argue that the results of past studies are largely affected by a survival bias (survival for innovation, instead of innovation for survival), and find that the positive relationship between innovation and survival turns negative once statistical controls are adopted to eliminate such bias.

In this paper, we empirically investigate the relationship between patents and the survival of young firms by using datasets linking the Japanese economic census and patent database. First, we carefully controlled for selection bias. Because our empirical results are based on census data, which covers entire population of firms located in Japan, we are able to provide sound evidence for the relationship between innovation and survival without fear of selection bias. In addition, we also control for possible survivorship bias of ideas (Hyytinen et al., 2015). That is, if output measures for innovation such as new products are used, commercial success of innovation may be achieved because a firm can survive longer (survival for innovation, instead of innovation for survival). We use patent application as a proxy for firms' innovation activities, while controlling for patent quality by using the timing when patents are granted.

The second contribution of our study is to look in detail at the organization of innovation activities, i.e., whether firms engage in innovation by themselves or do they collaborate with other firms or universities. We do this by measuring joint patent applications. In the era of open innovation, more and more firms collaborate with other firms to facilitate R&D (Chesbrough, 2003). Collaboration in innovation activities affects the relationship between patents and firm survival in two different ways. Collaborating with other firms may mitigate the commercial and financial risks associated with innovation (positive impact on firm survival). At the same time, collaborating with other firms may increase the complexity of innovation management, which has a negative impact on survival (Rosenbusch et al., 2010). We investigate this tradeoff with respect to open innovation. In addition, since we are able to identify in our datasets the manner in which firms exit, i.e. whether the exit is due to acquisition by another firm or firm dissolution, we exclude instances of exits due to M&A, which may

cause potential bias on account of the positive association with joint patent application.

This paper is structured as follows. First, we introduce theoretical aspects of industrial dynamics and empirical literature to explain the relationship between firm innovation and survival. In addition, hypotheses are offered of the relationship between patents and firm survival according to the way in which innovation is organized. Then, we follow with a description on the dataset for this study, which comprises the Enterprise and Establishment Census data and the JPO patent database. Next, we show the results of a quantitative analysis to test the hypotheses developed in the section 2. Finally, we summarize our findings and provide a discussion and policy implications.

2. Theory and Hypotheses

The theoretical models of firm exit or survival are based on competition between new and existing players in the market, taking into account firms' heterogeneous capabilities. The passive learning model explains the industrial dynamics of the process through which a firm learns its own initially endowed capabilities, which it was not aware of at the time of entry (Jovanovic, 1982). In accordance with the Bayesian inference of past market experience, a firm has to make a decision during each period on whether to continue or exit based on a belief on its capability. When a firm overestimates its capability, it may overinvest to grow faster, but this increases the probability of failure and market exit. Therefore, the rate of exit decreases along with a firm's age as it learns the level of its own capabilities through market experience over time.

The active learning model, instead, takes into account the fact that firms' capabilities are not only determined by their initial endowment, but subsequent investments (Ericson and Pakes, 1995). Here as well, in every period, a firm has to make a decision whether to continue or exit, but it also decides on the level of investment when it decides to continue to operate. In this model, there are two state variables, the level of competency (positively correlated with firm outcome) and the number of firms with the same level of competency (negative correlated with firm outcome). The Markov process is assumed in dynamics, in the sense that a firm's perception of own and its competitors' states is based only on the previous period. The level of investment for next period is determined by dynamic optimization to maximize firm value with an exit option. An exit option is executed when the value of firm becomes less than an opportunity cost of staying in the market (outside value of the firm). There are also entrants to this market, when the expected value of entry exceeds the fixed cost of entry.

The pattern of industry dynamics, referring to entry, continuation and exit, appears quite different in the passive learning and active learning models. In the former, firm

growth patterns are described as the path that firms take to reach a certain scale, depending upon their endowed capacity (larger endowment leads to larger size) amid continuous entry and exit flux, particularly among young firms which do not precisely know their capabilities. In terms of the relationship between innovation and survival, the passive learning model assumes that firms gradually learn their capabilities, so that their survival rate increases over time, and firm capability levels and survival rates are generally positively correlated. In contrast, the active learning model illustrates a more dynamic picture with continuous changes in firms' relative positions and firm may exit regardless of their age. Technological capability is attained through investment, but the survival rate of firms depends also on market environment, so that risky investments in technology may turn out to be unfavorable in some cases.

The reality is, of course, in between these two. Firm level analyses of productivity studies show the ranking order of productivity is persistent over time (Baily et al., 1992; Bartelsman and Doms, 2000), and exit is likely to occur more among younger firms (Bartelsman et al., 2005). However, a firm's growth cannot be solely determined by its initial endowment, but also is serially correlated to efforts to improve capabilities over the long term. The assumption of Markov process in Ericson and Pakes (2005) is too strong, the impact of investment stays over time does not disappear instantly after the subsequent investment. But it does not stay over firm's entire life, suggested by the theory in Jovanovic (1982), either.

Empirically, the relationship between innovation and survival is positive in many studies. Esteve-Perez and Manez-Castillejo (2008) and Orgega-Argiles and Moreno (2007), which use R&D as an index for technological capability, show a positive relationship between R&D and company survival, which has especially been seen in the hi-tech industry. Moreover, Cockburn and Wagner (2007) and Helmers and Rogers (2010) use patents as an indicator of innovation, and both studies found a positive relationship. Cefis and Marsili (2005), which was based on Dutch Community Innovation Survey data, found that successful innovation by firms leads to a higher survival rate, particularly in the case of process innovation.

However, recent studies have made revealed that this positive relationship is context based, and this relationship turns into negative in some cases (Hyytinen et al., 2015). For example, Buddelmeyer et al. (2010) analyzes the impact of patent application and patent stock separately, and finds a negative impact from recent patent applications on firm survival, after controlling for the impact of patent stock (with its positive relationship with firm survival). They argue that the uncertainty involved in radical innovations surpasses the capability effect implied by patenting. A negative relationship between patents and firm survival has also been found by Motohashi (2016) and Pederzoli et al. (2011). Since a patent should involve any technological contents new to

the world is developed, its applicant firm is supposed to conduct substantial “exploration” activities, rather than “exploitation” activities, which does involve technological and/or commercial risks (March, 1991). Therefore such risky investments may lead to less survival rate for firms with patenting activities.

Broadly speaking, there are two types of uncertainty associated with innovation: technological risk and commercial risk. Technological risk is found in research and development as such activities do not always lead to a successful conclusion. When a firm reaches the point of filing for a patent, it has overcome such technological risk, but commercial risk is still present in that not all patents result in commercial successes. Therefore, the findings in Buddelmeyer et al. (2010), Motohashi (2016) and Pedezoli et al. (2011) may be explained mainly due to the substantial commercial risk entailed in patented technologies. However, firms filing more patents are also more likely to have superior technological capabilities. This is particularly true in cases where a firm’s patents has a high commercial value. It has been found that a patenting entrepreneur is more likely to receive venture capital financing. Patenting may have a signaling effect to potential investors that also improve the firm’s survival rate (Haeussler et al., 2009). A positive relationship between patenting and survival has also been found in empirical literature (Helmers and Rogers, 2010). Therefore, our hypotheses on the relationship between patenting and firm survival are:

H1: The impact of patenting on a firm’s survival is determined by balancing the level of uncertainty in innovation (negative) and technological capability (positive).

H1a: When a firm has strong technological capabilities, patent filing is likely to have a positive impact on the firm’s survival.

H1b: When a firm files a patent which is sufficiently valuable in the market, a positive impact from the patent filing on firm survival is more likely, since commercial risk is relatively smaller.

Moreover, open innovation, which is external collaboration with other firms on R&D, may mitigate the risk associated with innovation, since both technological and commercial risks can be shared with the partner. Zheng et al. (2010) explains two types of benefits from inter-firm networks for entrepreneurs: (1) transferred benefit and (2) perceived benefit. A higher failure rate for young firms can be explained by the fact that they have yet to fully develop a routine and policy for managing business uncertainty. Transferred benefit refers to the “pipe” through which partners transfer information and knowledge to overcome uncertainty. In addition, there is a perceived benefit from inter-firm network, which works as a “prism” signaling the quality of firms’ management of partner relationships (Zheng et al., 2010).

However, R&D collaboration induces more complexity into innovation management such that the rate of success tend to decrease (Rosenbusch et al., 2010). Bederbos et al. (2010) shows the negative relationship between the degree of co-patenting and firm value. They argued that potential R&D collaboration disadvantages, such as coordination costs and reduced potential future revenue due to co-ownership of technology, may surpass potential benefits, such as access to new technologies and lower technology commercialization risk. This is particularly true in cases where a firm is young, has limited management resources and less experience managing alliances. Therefore, our hypotheses about R&D collaboration and firm survival are:

H2: The impact of open innovation on firm survival is determined by the balance between positive factors, such as risk sharing and transferred benefit, and negative factors, such as management complexity and coordination cost.

H2a: Positive factors surpass negative factors when firm size is larger, since management complexity can be overcome with more resources.

H2b: Positive factors surpass negative factors when a firm's capability for technological development is greater, since the firm's absorptive capacity allows it to capture more transferred benefits from its partner.

3. Dataset and descriptive statistics

In order to conduct an empirical analysis of patenting and firm survival, we have constructed the dataset linking Japan's Statistics Bureau's Enterprise and Establishment Census and the IIP Patent Database, compiled by using the JPO's patent information.

The Enterprise and Establishment Census encompasses all business establishments in Japan. Along with providing basic statistical data such as the number of establishments and employees, it is also used as the survey body information set for the other governmental statistical surveys. This survey is conducted twice every five years, and was known as the Establishment Census until July 1991. With the October 1996 survey, the name was changed to the Enterprise and Established Census. Also, since the October 1996, the addition of "head office address" as a survey item allows for grouping of business establishments by company name and address. The Enterprise and Establishment Census was conducted every 5 years (and one preliminary survey in-between 5 year period) until 2006, when the Japanese government decided to use the "The Economic Census," which is based on the concept of firm level identification of economy activities instead of establishment level, for the next round. In 2009, a similar preliminary survey was conducted, which was called the "Preliminary Economic Census Survey," after which the first Economic Census was conducted in 2012.

The IIP Patent Database is compiled based on Consolidated Standardized Data, which is made public twice a month by the Japan Patent Office. The Consolidated Standardized Data includes patent information recorded as a text file with SGML and XML tags. In this study, we use the IIP Patent Database in which the text files released by the JPO are converted to an SQL database to allow easier statistical processing of the data. As of December 2016, this included information made public from January 1964 until March 2014, which was able to be downloaded on the Institution of Intellectual Property (IIP) website (<http://www.iip.or.jp>). The IIP patent filings, publicly released data in CSV-format, includes patent application data (application number, application date, examination request date, technological field, number of claims, etc.); patent registration data (registration number, rights expiration date, etc.); applicant data (applicant name, applicant type, country/prefecture code, etc.); rights holder data (rights holder name, etc.); citation information (citation/cited patent number, etc.); and inventor data (inventor name, address) (Goto and Motohashi, 2007).

Linkage between the Enterprise and Establishment Census and IIP Patent Database used identical company names (standardized one) and locations². In this study, because firm level establishment identification was not complete in the surveys before 2001, we use two Enterprise and Establishment Census surveys, one from 2001 and one from 2006, as well as the Economic Census from 2012. The number of all firms in this dataset is 5,336,971 in 2001, 4,897,132 in 2006, and 4,608,794 in 2012, and the number of firms with patent applications is 84,035 (1.57%) in 2001, 82,471 (1.68%) in 2006, and 72,648 (1.58%) in 2012.

Since the Economic Census provides longitudinal information at the establishment level instead of the firm level, we have to construct firm dynamics, i.e., entry, exit and continuation, between survey periods. At the establishment level, longitudinal linkage information between two periods is available, and firm level information identifying each establishment (for firms with multiple establishments) is also available in each survey. We utilize the following rules to identify the same firm in two successive surveys: (1) if all establishments belonging to one firm in a survey can be connected to all establishments belonging to one firm in the subsequent survey, then these two firms are identical, and (2) if establishments belonging to a firm in a survey belong to two or more firms in the subsequent survey, we regard the firm with the largest number of establishments linked in the subsequent survey as being identical to the previous one.

A novel feature of this dataset is the distinguishability of the type of firm exit, i.e.

² A detailed description of the linkage of census and patent data can be found in Ikeuchi et al. (2017).

whether it is a complete shutdown (dissolution) or acquisition by another firm (acquisition). When a firm is completely shut down, all establishments belonging to the firm disappear in the subsequent period. However, when a firm is acquired by another firm, some of the establishments belonging to the acquired firm are expected to belong to the other firm in the subsequent period.

Table 1 shows the sample size of the dataset used. Our focus is on young firms' patenting and survival, so we selected firms that were no more than 5 years old, which amounted to approximately 650,000 to 800,000 firms, out of roughly 5 million firms located in Japan. Among these selected young firms, those with patent applications numbered approximately 7,000. For example, 6,118 (3,162 surviving, 2,761 dissolved, and 195 acquired) firms filed patents out of a total of 658,121 (313,403 surviving, 307,384 dissolved, and 37,334 acquired) firms in 2006. The share of surviving firms is higher for firms with patents because the average size is greater for firms in that sample. Table 1 also shows that the sample size of the firms filing joint patent applications with other firms (inter-firm networks) and those collaborating on patents with universities (Industry-University (IU) collaborations). The share of surviving firms collaborating on patents is higher than that of the firms holding patents in general, but the share of acquisitions is also higher for firms with inter-firm networks and IU collaboration.

(Table 1)

Table 2 shows patents and survival by firm size, which is measured by the number of a firm's employees at the beginning of periods. The survival rate increases as firms become larger in the case of firms holding patents in both sample periods, while the survival rates of larger firms (those with more than 100 employees) are relatively low, particularly in the later period from 2006 to 2011.

(Table 2)

Tables 3 shows firm distribution by industry. The industries, in which a high number of patent applications are held, are the information and communications, the manufacturing, and the electricity, gas, heat supply and water industry. Moreover, the share of patenting firms has increased across all industries. When we look at survival rates, we see that patenting firms have higher survival rates in almost all industries in 2001 with the exception are service N.E.C. and medical service. However, in the period from 2006 to 2012, patenting firms showed more exits in several industries, including agriculture, forestry and fisheries and the electricity, gas, heat supply and water industry.

(Table 3)

4. Econometric Analysis

In this chapter, an econometric analysis is conducted to test the hypotheses laid out in Section 2. Our dataset has three data points (2001, 2006 and 2012), and the basic strategy is to compare firm survival and exit in two periods (2001-2006 and 2006-2012) using firms' patenting activities at the beginning (2001 or 2006)³. Specifically, the dependent variable in our econometric model is a binary variable using either 1 (for survive) or 0 (for exit), and we pool all samples in two period to run probit regression with several explanatory variables, which is explained later. It should be noted that there is no overlap of samples in these two periods because we use firms that are no more than 5 years old at the beginning (a firm established before 2001 is already more than 5 years old at the time of the 2006 survey, so it is not included with the samples for the 2006-2012 period).

The key explanatory variables in this study are constructed using patent data. In order to avoid any survival bias caused by patenting (survival for patenting, instead of patenting for survival), we use a dummy variable (*d.ap0*) for whether a firm applies for any patents prior to the beginning time (*T0*). Most of studies investigating the relationship between patenting and survival use patent applications (and/or stock of registered patents) at the time of firm exit (Helmers and Rogers, 2010; Cockburn and Wagner, 2010). In this case, the longer a firm survives, the more likely it is to apply for patents. Therefore, the relationship between patent and survival tends to be positive (Hyytinen et al. 2015). In order to avoid such reverse causality, we set a starting line for all firms, and take into account only patents applied before this time so that we may more clearly observe the impact of patent on survival. We also control for firm size (log of employment), log of firm age and its cross term at the beginning time (*T0*).

In order to identify a patent that have potential market viability, we construct additional patent statistics using patent grant time (Figure 1). Under Japan's patent system, a patent applicant has to request a patent examination in order for the patent to be granted within 3 years after application⁴. However, if an applicant perceives great potential in terms of the patent's market applications, the applicant is supposed to request an earlier examination so that this patent to be granted as soon as possible. Therefore, patents granted soon after application tend to have greater market potential than those granted later. In addition, such patents may be superior in terms of technology

³ The timing of the surveys is October 1 for the 2001 and 2006 surveys, and February 1 for the 2012 survey. Therefore, it should be noted that the first period spans only 5 years while the second is a bit longer at 5 years and 4 months.

⁴ The duration of this period used to be 7 years, but it was shortened for patents applied for after October 1, 2001.

as well. A short duration between patent application and grant means that the patent passed examination without any refusal actions initiated on the initial application. Therefore, we use the variable `d.ap0_grXyr`, which refers to a dummy variable if a patent is granted before X years have passed since its application.

(Figure 1)

It should be noted that `d.ap0_grXyr` can be positively biased toward surviving firms because when X is lengthened, surviving firms have more time for their patents to be granted. Figure 2 shows how `d.ap0_grXyr` changes when X gets longer. It should be noted that `d.ap0_grXyr` values across survival status diverge when X gets longer. The difference, particularly after X is 5 years and longer, between firm survival and exit, may reflect a survival bias (survival for patent grant) in this indicator. We will come back to this point again when discussing the regression analysis results.

(Figure 2)

In addition, we have constructed two types of variables from the patent database: a dummy variable for joint applications or joint inventions with universities (`d.univ0`) and a dummy variable for joint applications with other firms (`d.firm0`). The former variable can be used as a proxy for firm technological capability. The share of firms jointly working together with universities increases from 0.02% in 2001 to 0.07% in 2006, reflecting the incorporation of national universities in 2004 (Motohashi and Muramatsu, 2012). These firms are a small set which have enough technological capability (absorptive capacity) to collaborate with academia. In contrast, joint patent application with other firms has not much increased (0.3% in 2001 and 0.4% in 2006). This variable reflects collaboration on innovation for business. Table 4 shows descriptive statistics for these variables.

(Table 4)

We run regressions for pooled datasets for two time periods (2001-2006 and 2006-2012), and include the interactions of time dummies and industry dummies in our regression models in order to control for the different impact of macro-economic changes over time by industry. Just as with the patent-related variables explained above, we control for firm size according to the number of employees as well as firm age and the interaction of these two at the beginning of the observation period. Probit regression results in all tables are converted to marginal effect. As is seen in the Model (1) in Table 5, the coefficient of `d.ap0` (ex-ante patent application dummy) is positive and statistically significant at 1%. However, it should be noted that firm exits due to acquisition are included in this model. A start-up firm with higher technological capability can be an

attractive target in the M&A market. The differences in firm exit antecedents between dissolution and acquisition have been investigated in the past (Mitchell, 1994; Grilli et al., 2010). Srinivasan et al. (2008) extends these studies by taking into account firms' technology management strategies, and finds a positive relationship between the a firm's technological capability and firm exit due to acquisition, while such relationship turns negative for firm exit due to dissolution. When we ran regression separately for firm exits due to acquisition (Model (2)) and dissolution (Model (3)), we found that the impact of d.ap0 is larger for acquisition sample (0.0667), as compared to the one for and not dissolution sample (0.0117), which is consistent with past literature.

(Table 5)

Hereafter, we focus on the survival rate, comparing exit due to dissolution (excluding the acquisition sample) to investigate the vulnerability of young firms more precisely. First, we test the possibility of survival bias by using patent application at the time of exit. We do not have precise information on exit timing, so we use a dummy variable for patent applied through year end (d.ap1). As expected, the coefficient of d.ap1 is positive and statistically significant (Model (4)), and when we include both d.ap0 and d.ap1, then the coefficient of d.ap0 turns out to be negative and statistically significant (Model (5)). We have confirmed a survival bias associated with d.ap1 (survival for patenting, instead of patenting for survival), which also affects the coefficient of d.ap0. Hereafter, we focus on ex-ante patenting activities in the observation period for firm survival. In Models (6), (7) and (8), we include dummy variables for collaboration on inventions. Generally speaking, university collaboration as a representation of firms' technological capability has a positive impact on firm survival as long as the coefficient of collaboration with other firms is positive, but it is hard to say that this is statistically significant.

Table 6 shows regression results including for d.ap0_grXyr, a dummy variable expressing whether or not an application patent before T0 is granted within X years after application, as well as a dummy variable expressing whether firms collaborate with universities (d.univ0), which is a reflection of firms' technological capability (absorptive capacity). First, all of coefficients of d.univ0 are positive and statistically significant, so that H1a is supported. In addition, positive and statistically significant coefficients are found with all variables of d.ap0_grXyr. In addition, the coefficient of d_ap_grXyr decreases as X increases up to X=3. This is consistent with the view that patents with a shorter grant lag have a relatively greater potential market value such that H1b is supported. The reason why the coefficient of d_ap_grXyr increases again after X=4 is that the degree of survival bias becomes larger as X gets longer (survival for patent grants, instead of patent grants for survival). As is discussed earlier with regard to Figure 2, this bias becomes greater, particularly after X is more than 4 years.

(Table 6)

Table 7 shows regression results including collaborative patent variables. Here, $d.firm0$ and $d.univ0$ interact with $\ln.emp$, and a moderation effect is observed of ex-ante firms' management resources with firm survival during the observation period in terms of the relationship between open innovation and survival. When we include only interaction of $d.firm0$ and firm size, then the coefficient of these cross terms is positive and statistically significant, while the coefficient of $d.firm0$ is negative and statistically significant (Model (7)). This means that joint technological development with other firms has a negative impact on survival of very small firms, while it is positive for larger firms. When the interaction of $d.univ0$ and firm size are also included (Model (3)), a similar patterns for joint technological development with universities emerges, while the negative coefficient of $ap.firm0$ is not statistically significant. We have consistent results even when controlling for potential market value (d_ap0_grXyr variables) (Models (4) and (5)). Therefore, the resource requirements to make collaborative projects successful is more intense for university collaboration than for collaboration with other firms.⁵

(Table 7)

As for $d.firm0$, firms reduce liability related to novelty by collaborating with other firms in a sense that they may be able to rely on the counterpart's managerial resources (market channels, financial resources etc.). On the other hand, collaborating with other firms increases the complexity of managing innovation. Such negative factors decrease as firm size increases, so that the overall effect of collaboration with other firms turns positive for larger firms, and vice versa (supporting H2a). In terms of $d.univ0$, reflecting firms' technological capability, larger firms will be able to capture market opportunities from technology sourcing from universities more easily because such firms tend to have a better capability to absorb and appropriate fundamental knowledge from academia (supporting H2b). In addition, a stronger moderation effect due to firm size with university collaboration may suggest that innovation with universities is riskier both technologically and commercially.

5. Discussion and Conclusion

This paper uses a dataset linking the Economic Census and IIP Patent Database for Japanese firms to conduct a systematic analysis of the relationship between patenting and firm survival. We have disentangled two competing factors associated with

⁵ When we divide the sample according to firm size, the effects of collaboration with a university or other firm on survival are positive and statistically significant for firms with 50 or more employees, while they are not significant for small firms with less than 50 employees (see Appendix Table 1).

innovation, which are technological capability (positive influencing firm survival) and commercial risk (negative influencing firm survival), and found that positive impacts generally surpasses negative ones, and such tendency is stronger when patents have relatively greater potential market value, even after controlling for various possible causes of survival bias.

In addition, we have investigated whether collaboration with universities and/or other firms helps firm survival in terms of innovation. We found that collaboration with universities reflect firms' technological capability to absorb scientific knowledge from the academic sector and leads to higher probability of survival, while the requirement of complementary resources for successful innovation is quite intense and the survival rate is even smaller for small firms engaging in university collaboration. In comparison with university collaboration, the impact of collaboration with other firms on survival is modest, and, again, firm size positively moderates the relationship between patenting and survival. That is, a certain level of managerial resources for overcoming complexity associated with open innovation is required to gain from such collaboration.

Innovation is essential to firms' growth and productivity, but failure of a risky investment may lead to failure of the firm itself. We would expect a learning effect from innovation even if it ends in failure, but when a firm exits due to dissolution, the experience gained from such innovation is lost as well. Therefore, we expect a substantial social welfare loss associated with exit of firms investing in risky R&D projects (Knott and Pose, 2005). However, our finding of a positive impact on survival from patenting, even for fragile young firms, is encouraging for policy makers promoting high-tech entrepreneurship. While the survival rate for young firms is relatively lower and many young firms simply go through the revolving door of the market, firms engaging in innovation are more likely to stay in the market and serve as a source for job growth.

However, it should be noted that open innovation, as understood in terms of joint technological development with other firms, does not always lead to a higher likelihood of survival. The resource requirement for university collaboration is intense, so engaging in innovation with universities is more likely to have negative consequences for small firms. This may be due to the fact that a project involving university may take longer to reach the market, requiring substantial financial resources. Our results suggest the existence of financial and labor market failures associated with young firms involved in collaborative projects with universities, which are likely to be university based start-ups, and some policy action is advised to correct market imperfections.

Collaboration with other firms is more commonly observed in our sample, but we found that obtaining value from joint technological development requires that firms have

a certain minimum amount of managerial resources as well. One difference between inter-firm collaboration and university collaboration is that the former tends to focus more on market application, and may be beneficial for young firms by benefiting from a partner's assistance to reduce market risk. However, joint innovation involves substantial management complexity (Rosenbusch et al., 2011), and managing such a process is particularly difficult for young firms with less experiences and resources (Kale et al., 2002). Therefore, possible policy actions include managerial advice on open innovation and collaborative R&D projects sharing best practices for young and small firms.

Finally, we conclude this paper with some limitations. First, because this study is based on periodically conducted survey data (5-year spans), information detailing the exact time of firm dissolution is not available. Therefore, survival bias cannot be completely controlled. Results on the relationship between innovation and firm survival that are inconsistent with past empirical studies are largely explained in terms of the treatment of survival bias (Hyytinen et al., 2015). This is the reason why we made a substantial effort to employ patent examination process data, but a more systematic study could be done if information on firms' exit timing were included, which might be found, for example, in administrative records on tax reporting. Second, we use patent information as a proxy for innovation. At the patenting stage, technological risks still remain as well as commercial risks until the innovation results in new product sales. Additional information on innovation, such as product innovation, would allow us to disentangle commercial risk from technological risks in our analysis, which would have more precise implications for management policy.

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Figure 1: Construction of patent variables

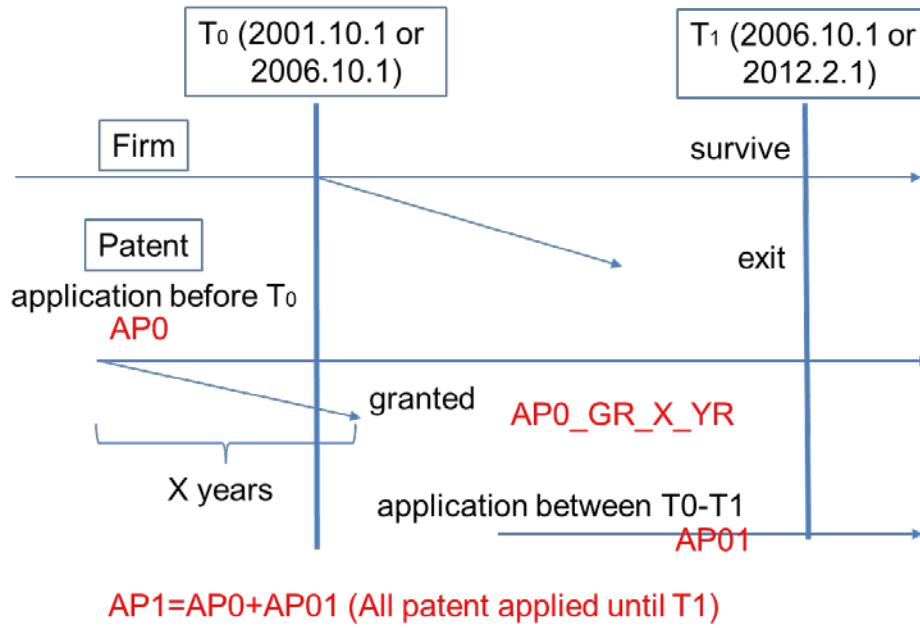


Figure 2: Share of firms with a patent application granted after X year(s) by survival status

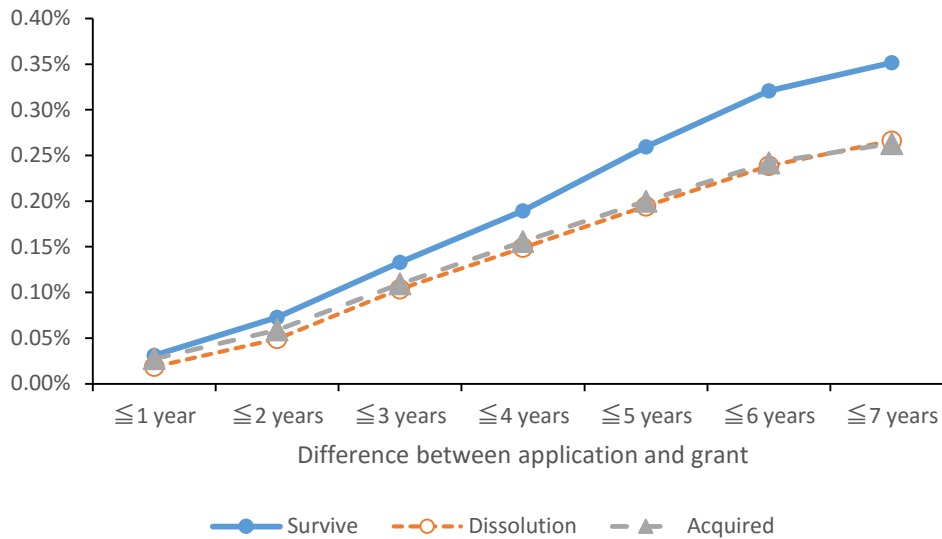


Table 1: Sample size

	All firms		Firms with patents		Inter-firm network		I-U collaborations	
	01-06	06-12	01-06	06-12	01-06	06-12	01-06	06-12
Dissolution	405,896	307,384	3,234	2,761	1,171	1,037	70	173
Survival	387,754	313,403	2,914	3,162	1,106	1,343	85	288
Acquired	10,188	37,334	67	195	28	98	1	25
Total	803,838	658,121	6,215	6,118	2,305	2,478	156	486
<u>Share of the firms by survival status</u>								
Dissolution	50.5%	46.7%	52.0%	45.1%	50.8%	41.8%	44.9%	35.6%
Survival	48.2%	47.6%	46.9%	51.7%	48.0%	54.2%	54.5%	59.3%
Acquired	1.3%	5.7%	1.1%	3.2%	1.2%	4.0%	0.6%	5.1%

Table 2: Patent and survival by firm size

Size	# of firms				Survival rate			
	All firms		Firms with patents		All firms		Firms with patents	
	01-06	06-12	01-06	06-12	01-06	06-12	01-06	06-12
1	162,717	132,898	404	373	45.1%	47.2%	43.1%	42.4%
2	151,326	112,044	516	514	46.9%	49.6%	44.6%	42.2%
3	104,345	80,884	553	536	45.8%	46.1%	45.9%	45.1%
4-5	133,194	107,118	967	860	48.1%	46.7%	44.8%	48.3%
6-10	134,161	112,818	1,438	1,270	50.7%	48.3%	46.3%	49.6%
11-100	114,199	106,614	2,097	2,138	53.7%	48.1%	48.4%	55.6%
101-1000	3,830	5,571	234	393	56.8%	37.6%	58.5%	72.0%
1001-	66	174	6	34	53.0%	38.5%	83.3%	85.3%
Total	803,838	658,121	6,215	6,118	48.2%	47.6%	46.9%	51.7%

Table 3: Patent and survival by industry

Industry	# All firms		Firms with patents		Survival rate			
	01-06	06-12	01-06	06-12	All firms		Firms with patents	
					01-06	06-12	01-06	06-12
A/C Agriculture, Forestry and Fisheries	1,865	1,805	0.7%	0.8%	69.2%	61.9%	76.9%	46.7%
D Mining	166	94	0.6%	1.1%	47.6%	53.2%	100.0%	0.0%
E Construction	46,488	29,370	0.9%	1.4%	50.0%	54.5%	55.4%	55.3%
F Manufacturing	37,888	25,882	3.2%	5.1%	50.3%	53.7%	55.9%	58.7%
G Electricity, Gas, Heat Supply and Water	96	129	3.1%	3.9%	61.5%	52.7%	66.7%	20.0%
H Information and Communications	17,268	12,600	5.2%	6.2%	29.7%	33.7%	31.7%	42.9%
I Transport	12,131	8,865	0.4%	0.6%	52.6%	50.1%	56.9%	41.8%
J Wholesale and Retail Trade	194,249	140,018	0.9%	1.0%	44.5%	43.8%	47.2%	49.2%
K Finance and Insurance	9,776	9,136	0.8%	0.8%	42.3%	37.7%	42.7%	40.8%
L Real Estate	31,141	21,048	0.5%	0.8%	56.4%	54.9%	61.2%	55.2%
M Eating and Drinking Places, Accommodations	217,920	167,007	0.2%	0.2%	42.4%	45.4%	51.3%	54.0%
N Medical, Health Care, and Welfare	59,448	71,631	0.1%	0.2%	67.7%	59.9%	57.1%	67.9%
O Education, Learning Support	26,908	23,728	0.2%	0.6%	50.1%	50.2%	51.0%	70.4%
P Compound Services	4,812	22,795	0.2%	0.0%	60.6%	2.4%	66.7%	71.4%
Q Services, N.E.C.	143,682	124,013	0.9%	1.0%	52.3%	53.3%	41.5%	47.8%
Total	803,838	658,121	0.8%	0.9%	48.2%	47.6%	46.9%	51.7%

Table 4: Descriptive statistics

Variable	Definition	Year=2001 (n=793,650)				Year=2006 (n=620,787)			
		Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Survive (5 years)	1 if the firm survives at T1; 0 otherwise.	0.4886	0.500	0.0	1.0	0.5048	0.500	0.0	1.0
ln.emp	ln. # of employees	1.2881	1.004	0.0	8.6	1.3141	1.045	0.0	8.7
ln.age	ln. firm age	0.7494	0.613	0.0	1.6	0.7689	0.616	0.0	1.6
d.ap1	1 if # of patent applications of the firm at T1 > 0; 0 otherwise.	0.0114	0.106	0.0	1.0	0.0126	0.112	0.0	1.0
d.ap0	1 if # of patent applications of the firm at T0 > 0; 0 otherwise.	0.0077	0.088	0.0	1.0	0.0095	0.097	0.0	1.0
d.ap0_gr1y	1 if # of patent applications of the firm at T0 within 1 year > 0; 0 otherwise.	0.0002	0.014	0.0	1.0	0.0003	0.017	0.0	1.0
d.ap0_gr2y	1 if # of patent applications of the firm at T0 within 2 year > 0; 0 otherwise.	0.0005	0.023	0.0	1.0	0.0007	0.027	0.0	1.0
d.ap0_gr3y	1 if # of patent applications of the firm at T0 within 3 year > 0; 0 otherwise.	0.0010	0.032	0.0	1.0	0.0014	0.038	0.0	1.0
d.ap0_gr4y	1 if # of patent applications of the firm at T0 within 4 year > 0; 0 otherwise.	0.0015	0.038	0.0	1.0	0.0020	0.045	0.0	1.0
d.ap0_gr5y	1 if # of patent applications of the firm at T0 within 5 year > 0; 0 otherwise.	0.0019	0.043	0.0	1.0	0.0028	0.053	0.0	1.0
d.ap0_gr6y	1 if # of patent applications of the firm at T0 within 6 year > 0; 0 otherwise.	0.0021	0.046	0.0	1.0	0.0037	0.061	0.0	1.0
d.ap0_gr7y	1 if # of patent applications of the firm at T0 within 7 year > 0; 0 otherwise.	0.0022	0.047	0.0	1.0	0.0042	0.065	0.0	1.0
d.coapp_firm0	1 if # of patents co-invented at T0 > 0; 0 otherwise.	0.0029	0.053	0.0	1.0	0.0038	0.062	0.0	1.0
d.coapp_univ0	1 if # of patents co-invented with universities at T0 > 0; 0 otherwise.	0.0002	0.014	0.0	1.0	0.0007	0.027	0.0	1.0

Table 5: Regression results on firm's survival

(Base estimate, all samples, probit estimation marginal effects)

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	All	Survived vs Acquired	Survived vs Dissolution	Survived vs Dissolution	Survived vs Dissolution	Survived vs Dissolution	Survived vs Dissolution	Survived vs Dissolution
ln.emp	0.0235*** [0.000651]	-0.0315*** [0.000381]	0.0360*** [0.000669]	0.0358*** [0.000670]	0.0357*** [0.000670]	0.0360*** [0.000669]	0.0359*** [0.000670]	0.0359*** [0.000670]
ln.age	0.102*** [0.00104]	0.0166*** [0.000800]	0.0997*** [0.00106]	0.0997*** [0.00106]	0.0997*** [0.00106]	0.0997*** [0.00106]	0.0997*** [0.00106]	0.0997*** [0.00106]
ln.emp * ln.age	-0.00381*** [0.000631]	-0.000709** [0.000358]	-0.000432 [0.000655]	-0.00043 [0.000655]	-0.000369 [0.000655]	-0.000437 [0.000655]	-0.000439 [0.000655]	-0.000442 [0.000655]
d.ap0	0.0288*** [0.00440]	0.0667*** [0.00317]	0.0117*** [0.00444]		-0.0723*** [0.00821]	0.00505 [0.00562]	0.00857* [0.00455]	0.00378 [0.00564]
d.ap1				0.0334*** [0.00379]	0.0852*** [0.00701]			
d.firm0						0.0172* [0.00895]		0.0131 [0.00907]
d.univ0							0.0643*** [0.0203]	0.0596*** [0.0205]
Industry-year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,461,959	747,639	1,414,437	1,414,437	1,414,437	1,414,437	1,414,437	1,414,437
Pseudo R-squared	0.0526	0.232	0.0574	0.0575	0.0575	0.0574	0.0574	0.0574
DF	193	193	193	193	194	194	194	195
DF model	188	179	188	188	189	189	189	190
logLik.	-958882.6	-135885.6	-924057.7	-924022.2	-923983.4	-924055.8	-924052.6	-924051.6
logLik. (null)	-1012135.7	-176936.3	-980361.1	-980361.1	-980361.1	-980361.1	-980361.1	-980361.1
Chi-squared	106506.3	82101.4	112606.8	112677.7	112755.4	112610.5	112616.9	112619.0
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 6: Regression results on firm survival by patent grant timing
(Excluding exit firms by M&A, probit estimation marginal effects)

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
ln.emp	0.0359*** [0.000670]	0.0359*** [0.000670]	0.0359*** [0.000670]	0.0359*** [0.000670]	0.0359*** [0.000670]	0.0359*** [0.000670]	0.0359*** [0.000670]
ln.age	0.0997*** [0.00106]	0.0997*** [0.00106]	0.0997*** [0.00106]	0.0997*** [0.00106]	0.0997*** [0.00106]	0.0997*** [0.00106]	0.0997*** [0.00106]
ln.emp * ln.age	-0.000442 [0.000655]	-0.000446 [0.000655]	-0.000443 [0.000655]	-0.000444 [0.000655]	-0.000447 [0.000655]	-0.000454 [0.000655]	-0.000452 [0.000655]
d.ap0	0.00687 [0.00459]	0.00481 [0.00467]	0.00525 [0.00482]	0.00321 [0.00497]	-0.0041 [0.00518]	-0.00953* [0.00539]	-0.0107* [0.00552]
d.univ0	0.0567*** [0.0205]	0.0512** [0.0206]	0.0564*** [0.0206]	0.0536*** [0.0207]	0.0450** [0.0206]	0.0387* [0.0207]	0.0391* [0.0207]
d.ap0_gr1yr	0.0725*** [0.0265]						
d.ap0_gr2yr		0.0629*** [0.0174]					
d.ap0_gr3yr			0.0270** [0.0129]				
d.ap0_gr4yr				0.0299*** [0.0112]			
d.ap0_gr5yr					0.0517*** [0.0101]		
d.ap0_gr6yr						0.0598*** [0.00952]	
d.ap0_gr7yr							0.0572*** [0.00930]
Industry-year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,414,437	1,414,437	1,414,437	1,414,437	1,414,437	1,414,437	1,414,437
Pseudo R-squared	0.0574	0.0574	0.0574	0.0574	0.0574	0.0575	0.0575
DF	195	195	195	195	195	195	195
DF model	190	190	190	190	190	190	190
logLik.	-924048.8	-924046.0	-924050.4	-924049.0	-924039.4	-924032.9	-924033.6
logLik. (null)	-980361.1	-980361.1	-980361.1	-980361.1	-980361.1	-980361.1	-980361.1
Chi-squared	112624.5	112630.1	112621.4	112624.1	112643.3	112656.4	112654.9
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 7: Regression results on firm survival by joint application status
(Excluding exit firms by M&A, probit estimation marginal effects)

	[1]	[2]	[3]	[4]	[5]
ln.emp	0.0359*** [0.000670]	0.0358*** [0.000670]	0.0358*** [0.000670]	0.0358*** [0.000670]	0.0358*** [0.000670]
ln.age	0.0997*** [0.00106]	0.0997*** [0.00106]	0.0997*** [0.00106]	0.0997*** [0.00106]	0.0997*** [0.00106]
ln.emp * ln.age	-0.000442 [0.000655]	-0.000478 [0.000655]	-0.000481 [0.000655]	-0.000481 [0.000655]	-0.000485 [0.000655]
d.ap0	0.00378 [0.00564]	0.00427 [0.00564]	0.00478 [0.00564]	0.0039 [0.00566]	0.00255 [0.00569]
d.firm0	0.0131 [0.00907]	-0.0386*** [0.0145]	-0.0175 [0.0151]	-0.0183 [0.0151]	-0.019 [0.0151]
d.univ0	0.0596*** [0.0205]	0.0446** [0.0209]	-0.123*** [0.0404]	-0.124*** [0.0404]	-0.127*** [0.0404]
ln.emp * d.firm0		0.0229*** [0.00502]	0.0127** [0.00544]	0.0125** [0.00544]	0.0123** [0.00544]
ln.emp * d.univ0			0.0614*** [0.0128]	0.0602*** [0.0128]	0.0598*** [0.0129]
d.ap0_gr1yr				0.0586** [0.0269]	
d.ap0_gr2yr					0.0529*** [0.0177]
Industry-year dummies	Yes	Yes	Yes	Yes	Yes
Observations	1,414,437	1,414,437	1,414,437	1,414,437	1,414,437
Pseudo R-squared	0.0574	0.0574	0.0575	0.0575	0.0575
DF	195	196	197	198	198
DF model	190	191	192	193	193
logLik.	-924051.6	-924041.0	-924028.9	-924026.5	-924024.4
logLik. (null)	-980361.1	-980361.1	-980361.1	-980361.1	-980361.1
Chi-squared	112619.0	112640.1	112664.4	112669.2	112673.4
p-value	0.000	0.000	0.000	0.000	0.000

Appendix Table 1: Regression results on firm survival by firm size
(Excluding exit firms by M&A, probit estimation marginal effects)

	[1]	[2]	[3]	[4]
	All	1-9	10-49	50+
ln.emp	0.0359*** [0.000670]	0.0350*** [0.00102]	0.0391*** [0.00429]	0.0218** [0.00915]
ln.age	0.0997*** [0.00106]	0.0964*** [0.00122]	0.0868*** [0.0118]	0.158*** [0.0383]
ln.emp * ln.age	-0.000444 [0.000655]	0.00370*** [0.00104]	0.00191 [0.00420]	-0.0152* [0.00835]
d.ap0	0.00277 [0.00565]	0.00127 [0.00731]	0.00702 [0.0100]	0.0528*** [0.0195]
d.ap0_gr1yr	0.0701*** [0.0266]	0.0964*** [0.0374]	0.0271 [0.0483]	-0.000936 [0.0606]
d.firm0	0.011 [0.00910]	0.003 [0.0120]	-0.001 [0.0161]	0.0641** [0.0279]
d.univ0	0.0529** [0.0207]	-0.0286 [0.0318]	0.0101 [0.0360]	0.200*** [0.0481]
Industry-year dummies	Yes	Yes	Yes	Yes
Observations	1,414,437	1,177,730	210,530	21,536
Pseudo R-squared	0.0574	0.0544	0.0476	0.0913
DF	196	196	196	196
DF model	191	187	187	174
logLik.	-924048.1	-771298.6	-137482.5	-12972.6
logLik. (null)	-980361.1	-815710.8	-144355.2	-14276.7
Chi-squared	112626.0	88824.4	13745.5	2608.3
p-value	0.000	0.000	0.000	0.000