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Abstract

This study examines time-period and industry heterogeneity of innovation activity in Japan from 1964 to 2006 using patent data and non-consolidated firm data. This study focuses on the following three periods, based on changes of the Japanese patent system, in and non-manufacturing industries: I) before 1976; II) 1976–1987; and III) after 1988. Specifically, for each degree of patent protection in each industry, this study examines how innovation activities are affected by the following determinants found in the innovation literature: size, market competition, and search variety (depth and scope). Empirical results show that when using the entire sample from 1964 to 2006, the size effect on innovation is significantly positive. In addition, the effects of market competition and search variety on innovation are inverse-U. When considering time-period heterogeneity, the effects of size and search variety are similar to the entire period; however, the inverse-U effect of market competition is broken after 1988. On the other hand, when considering industry heterogeneity, the effects of size and search variety are similar to the entire sample, but differ between manufacturing and non-manufacturing industries. In addition, the effect of market competition is not statistically significant in either industry.

Key words: Innovation; Patent; Inverse-U relationship; Competition; Search for variety.
JEL classification: L10, L40, O31

1. Introduction

Understanding corporate innovation activities is a key topic, not only in the academic field, but also for industry and government. From the standpoint of competition policy, it is important to question how the degree of patent protection (i.e., appropriability condition) affects innovation activities. In Japan, from 1964 to the early 2000s, although there were more than a dozen revisions, key changes in patent filing activity took place three times: single claim system (before 1976); multiple claim system (1976-1987); the improved multiple claim system (after 1988) (Goto and Motohashi, 2007; Motohashi, 2004; Sakakibara and Branstetter, 2001). When focusing on patenting activities during the period, the number of patent application and registration tends to increase over time (Goto and Motohashi, 2007). Apparently, the strengthening of intellectual property protection encourages innovation activities in Japan. Based on this background, this study aims to further examine whether there is time-period and industry heterogeneity in innovation activities (i.e., patenting activities), focusing on the basic determinants discussed in the innovation literature.

The motivation of this study is to examine whether changes in the degree protections in Japan's patent system affect Japanese firms' innovation activities. Since the last half of 1990s, following developments in the U.S. and other developed countries (such as effect of Agreement on Trade-Related Aspects of Intellectual Property Rights in the Uruguay Round of General Agreement on Tariffs and Trade in 1995), patent policy in Japan has shifted from an anti-patent policy toward a pro-patent policy (i.e., "IP-based Nation" was formulated in 2002 by Former Prime Minister Junichiro Koizumi). After the enactment of the Science and Technology Basic Law in 1995, the Intellectual Property Basic Act was enacted in 2002, and Intellectual Property Strategy Headquarters and Intellectual Property High Court were established respectively in 2003 and 2005. From these enforcements of policy, Japan is considered to progressively reinforce intellectual property protection. Against this pro-patent policy, however, the current trend of innovation in the world is moving toward the era of open innovation, and strict protection of intellectual property also has a harmful effect on innovation. Therefore, Japan will need to review this series of pro-patent policies sooner or later. To examine what type of effect on innovative activities will be caused by further protection of intellectual property, as at the first onset, this study aims to empirically investigate how the effects of innovation determinants in the literature have historically changed in Japan along with the changes in the degree of patent protection.

Corporate innovation studies have a long history beginning with Schumpeter (1942). Many studies in this field are associated with the Schumpeterian hypothesis, although test results for the Schumpeterian hypothesis are still considered inconclusive (for a comprehensive literature review, see Cohen and Levin, 1989; Gilbert, 2006; Cohen, 2010). Instead of the Schumpeterian view of innovation activity, in recent years, innovation search processes have focused on evolutionary economics. Laursen (2012) discusses that firms often need to access a variety of inputs to achieve successful innovation. Specifically, in this context, it is important to examine how firms manage exploitative search (or local search) and exploratory search (boundary-spanning or non-local search).

This study examines how and what types of determinants affect innovation activities in manufacturing and non-manufacturing industries, focusing on time-period and industry heterogeneity across the three periods: I) before 1976; II) 1976–1987; and III) after 1988. Specifically, this study uses firm data from 1964 to 2006, which consist of non-consolidated financial data and Institute of Intellectual Property Patent Database (IIP-DB). IIP-DB is based on the Japan Patent Office standardized data, and was developed by Institute of Intellectual Property[1] and Goto and Motohashi (2007).

This study aims to contribute to the literature in two ways: by using longitudinal data and analyzing basic determinants in the literature. When empirically examining determinants of innovation, as described above, inconsistent results are often found (Cohen and Levin, 1989; Gilbert, 2006; Cohen, 2010). This suggests that empirical results may depend largely on the sample conditions such as country, industry, or time-period. Among statistical or empirical studies examining innovation activities in Japan, representative studies are Ijichi et al. (2004, 2010), Inui et al. (2012), and Motohashi (2011, 2012). While these studies focus on short-term samples, this study uses longitudinal data from 1964 to 2006, divided into manufacturing and non-manufacturing

[1] http://www.iip.or.jp/e/e_patentdb/

industries. Inconsistent results in the literature also suggest that determinants of innovation may vary widely and be composite. However, to deepen the debate on the determinants, it will be more appropriate to use popular determinants in the literature than a wide variety of ad-hoc determinants. Therefore, this study uses basic and popular determinants. Concretely, they are size and market competition, which are classic factors in the industrial organization and exploitative and exploratory searches (search depth and scope, respectively), which has begun to garner attention in the evolutionary economics.

A short summary of this study follows. In terms of the entire sample during 1964-2006, size effect on innovation is positive. The size elasticity is approximately 0.22. In addition, the effects of Herfindahl-Hirschman Index (HHI; as proxy for market competition) and search depth and scope on innovation are inverse-U. When considering time-period heterogeneity, the effects of size and search depth and scope are similar to that of the entire period. The inverse-U effect of HHI, however, is broken after 1988. On the other hand, when considering industry heterogeneity, effects of size and search variety are also similar to the entire sample, but slightly different between manufacturing and non-manufacturing industries. In addition, the effect of HHI is not statistically significant in both industries.

The structure of this paper is as follows. Section 2 reviews the background of this study. This section firstly introduces the Japanese patent system and IIP-DB. Secondly, it discusses size and competition as innovation factors in the industrial organization and reviews Japanese studies. The section then introduces search variety in the evolutionary economics. Section 3 describes the empirical strategy and model, and Section 4 shows the data. Section 5 shows estimated results, and carefully checks each of determinants. Finally, Section 6 holds the conclusion.

2. Backgrounds

2.1 Patent system and innovation activity in Japan

From the standpoint of competition policy, it is important to question how the degree of patent protection (i.e., appropriability condition) affects innovation activities. Although Japan's patent laws have been revised multiple times, Japan's patent system has significantly changed three times from 1964 to 2006: single claim system (before 1976); multiple claim system (1976-1987); and the improved multiple claim system (after 1988) (Sakakibara and Branstetter, 2001; Motohashi, 2004).

Before 1976, Japanese patent law allowed for only one independent, single claim to be included in an invention. This system is not as popular in other developed countries. With a 1976 amendment to the patent law, the multiple claim system was implemented. In this system, a patent filing can have claims of possible embodiments (i.e., dependent claims); however, the degree of appropriability condition in this system is almost the same as it was in the single claim system. This is because the claims of possible embodiments are not intended to draw any boundaries of technical scope or patent rights. In the 1988 reform, the improved multiple claim system was implemented, making multiple claims possible in one application, similar to other countries. Note that in addition to the three periods, Goto and Motohashi (2007) argue that there is a large effect from the pro-grant opposition system to post-grant opposition system to patent filing activity from 1996 to 2003 (however, in 2004, the post-grant opposition system was revoked and an alternative new system of trial for patent invalidation was implemented).

Recently, the Institute of Intellectual Property and Goto and Motohashi (2007) developed IIP-DB based on the Japan Patent Office standardized data. Goto and Motohashi (2007) illustrated the trend of the number of registered patents in Japan over time (Figure 5, p.1436). The whole tendency of the registered patents is very few before 1976, flat or in uptrend from 1976 to 1987, increasing from 1988, jumping in proximity in 1996, and has been on a declining trend since about 2000. This indicates that as the degree of intellectual property protection is strengthened in a phased manner, innovation activities in Japan have been encouraged over time.

Based on the background of patenting activities in Japan, this study further examines how and what types of determinants affect innovation activities, focusing on time-period heterogeneity (or patent system heterogeneity) across the three periods: I) before 1976; II) 1976–1987; and III) after 1988. This study also considers industry heterogeneity between manufacturing and non-manufacturing industries because innovation activities may be different between the industries. Using IIP-DB, this study empirically examines possible determinants in the innovation literature. Candidates for the determinants are size and market competition, which are classic and popular in the industrial organization literature, and search variety (depth and scope), which has begun to garner attention in the evolutionary economics literature.

2.2 Size and market competition

Understanding the relationship between competition and innovation has long been a major focus of industrial organization, both theoretically and empirically (Cohen and Levin, 1989; Gilbert, 2006; Cohen, 2010). Schumpeter (1942) argued that more monopolistic firms can more readily perform research and development (R&D) activities because of reduced market uncertainty and more stable funding. Since then, many studies have examined the so-called Schumpeterian hypotheses that innovation activity is promoted by large firms and by imperfect competition (Kamien and Schwartz, 1975; Acs and Audretsch, 1987, 1988a, 1988b).

The former Schumpeterian hypothesis that large firms promote innovation activity is mainly supported in the literature (Cohen and Klepper, 1996; Cohen, 2010).[2] In particular, many studies have shown that the amount of R&D conducted by performers is closely related to the size of the firm, while R&D productivity declines with firm size (Cohen and Klepper, 1996). Meanwhile, Acs and Audretsch (1988a) argue that size factors such as firm size and R&D have disparate effects on large and small firms, implying that there is U-shaped relationship between innovation and firm size.

On the other hand, the latter Schumpeterian hypothesis that innovation activity is promoted by imperfect competition has been inconclusive, generally depending on the measures of

[2] In interpreting the positive function of firm size on innovation activity, there are primarily four views in the innovation literature (see Cohen, 2010): 1) larger firms can finance risky R&D more aggressively; 2) R&D function itself has economies of scales; 3) larger firms face larger markets, spreading innovation (fixed) costs over sales (i.e., cost spreading theory); 4) large and diversified firms have economies of scope or reduced risk related to innovation.

competition and innovation (see Cohen, 2010). To measure competition, empirical studies often use 1) traditional competition measures such as concentration and price-cost margin (PCM) (e.g., Horowitz, 1962; Scherer, 1967), 2) survey-based measures (e.g., part of Nickell, 1996), and 3) market-entry/exit measures (e.g., Motohashi, 2011, 2012). On the other hand, in recent decades, to measure innovation, empirical studies often use 1) R&D (as innovation inputs) especially in the early literature (e.g., Horowitz, 1962; Scherer, 1967), 2) other innovation measures such as the number of new products or patent measure (e.g., Acs and Audretsch, 1987, 1988a, 1988b; Blundell et al., 1999; Aghion et al., 2005), and 3) total factor productivity (TFP) measures (e.g., Nickell, 1996; Inui et al., 2012). Note that regarding relationship between competition and innovation, a negative relationship often refers to less competition or more concentration is associated with more innovation in line with Schumpeterian hypothesis, while a positive relationship is the opposite.

In the empirical studies, the relationship between competition (a lower degree of concentration) and R&D is most likely to be found as negative in line with the Schumpeterian hypothesis. Using a unique dataset, Horowitz (1962) found that in the more concentrated industries, firms are more likely to maintain research organizations and allow for higher research expenditures. Scherer (1967) also found that, in a general trend of the sample in manufacturing industries, market concentration ratio is positively related to the number of technical engineers plus natural scientists and R&D expenditures.

On the other hand, when using other measures of innovation output such as patents and TFP growth, the results often become ambiguous. A series of studies carried out in Acs and Audretsch (1987, 1988a, 1988b) serves as a useful reference. Acs and Audretsch (1987) used different measures of the number of innovations per employee between the large-firm and small-firm as the innovation rate, and found a negative relationship in line with the Schumpeterian hypothesis. On the other hand, Acs and Audretsch (1988b) used the raw value of the number of innovations per employee as the dependent variable, and found the innovation activity is discouraged by market concentration, suggesting a positive relationship. In addition, Acs and Audretsch (1988a), using the number of innovations as the dependent variable, found that the innovation activity is encouraged by large-firm employment share, but is discouraged by market concentration (i.e., positive relationship).

The positive relationship between competition and innovation is also found in other studies. Blundell et al. (1999) used a count of technologically significant and commercially important innovations of 3,551 observations in manufacturing industries listed in U.K., and found innovation is correlated positively with market share (i.e., in line with the Schumpeterian hypothesis), but negatively with industry concentration as in Acs and Audretsch (1988a). Also, Nickell (1996) adopted market share at the firm level and concentration ratio in the empirical model of the Cobb-Douglas production function. Using a total 676 observations in U.K. from 1972 to 1986, the author found TFP growth is positively correlated with competition.

Recently, Aghion et al. (2005) built a stylized model to support an inverse-U pattern between product market competition and innovation. The authors also empirically support this pattern using UK industry data (17 industries over the period from 1973 to 1994) using a kind of PCM measure as a competition measure. However, prior empirical studies that test for the inverse-U relationship have been inconclusive. Tingvall and Poldahl (2006) test the inverse-U relationship using Swedish manufacturing firm data from 1990 to 2000. The authors use firm-level R&D data as the innovation measure and HHI and PCM as competition measures. The result shows that the inverse-U relationship is supported by HHI but not by PCM. In addition, Correa (2012) analyzes how the establishment of the United States Court of Appeals for the Federal Circuit in 1982 has affected the relationship between innovation and competition. The author finds a structural break in the early 1980s, using the same dataset in Aghion et al. (2005). This indicates that there was a positive relationship during the period from 1973 to 1982, and a no-significance relationship in the period from 1983 to 1994, suggesting the existence of time heterogeneity.

2.3 Innovation studies in Japan

The inconclusiveness in the innovation literature suggests that innovation activity may depend largely on the sample. In terms of innovation studies in Japan, representative studies are Ijichi et al. (2004, 2010), Inui et al. (2012), and Motohashi (2011, 2012). These studies comprehensively examine innovation activity based on statistics or empirical analysis.

Ijichi et al. (2004, 2010) examine corporate innovation policies in all of Japan, using a questionnaire survey of 9,257 firms from 1999 to 2001 as the first survey (Ijichi et al., 2004) and 4,579 firms from fiscal years 2006 to 2008 as the second survey (Ijichi et al., 2010), in the agriculture, forestry and fisheries industry, mining and manufacturing industry, and service industry. Summarizing the surveyed results related to market competition, Ijichi et al. (2004) show that 74% of respondents replied that innovation activity is effective in increasing market share among companies that promote innovation activity, whereas 51% replied that innovation activity is not necessary because of their market circumstances among companies that do not promote innovation activity (Table 27, pp. 118-135). On the other hand, Ijichi et al. (2010) show that among companies that achieve product innovation (i.e., 43.9% of entire sample), 75.6% for Japanese market and 80.5% for the foreign market, replied that product innovation increases the market share from zero to five percent (Figure 4-11, p.40). These results suggest a mutual relationship between competition and innovation as in Aghion et al. (2005).

The other two studies are empirical studies, rather than statistical. Using Japanese comprehensive manufacturing data (from a basic survey of business activities of enterprises) from 1997 to 2003, Inui et al. (2012) examine the relationship between competition and innovation. The authors use PCM measure (i.e., 1−Lerner index as same as Aghion et al. (2005)) at the firm and industry average level as a proxy for competition, and TFP growth as a proxy for innovation. The result shows an inverse-U relationship in Japan.

Motohashi (2011, 2012) uses the IIP-DB and a census of establishment and enterprise from 2001 and 2006, empirically examining the relationship between the firm's survival and patent filing in Japan. The author argues that innovation may decrease or increase a firm's survival because innovation has two risks, technological and commercial. To examine whether firms surpass the commercial risk, the author assesses how patent filing (i.e., innovation) affects a firm's survival. The result of the probit regression model shows that commercial risk surpasses technological capability in these periods in Japan, which implies a positive relationship between competition and innovation.

When roughly classifying these three studies, Ijichi et al. (2004, 2010) and Inui et al. (2012) support the mutual or inverse-U relationship, whereas Motohashi (2011, 2012) indirectly supports the positive relationship. While the three studies analyze Japanese data for the short term, this study examines time-period and industry heterogeneity, using long-term data during the period from 1964 to 2006. Note that the IIP-DB is also used in Motohashi (2011, 2012). Specifically, this study focuses on the effects of size and market competition in each time-period in each of manufacturing and non-manufacturing industries.

2.4 Search depth and scope

In the evolutionary economics literature, Laursen (2012) argues that balancing exploitative search (or local search) and exploratory search (boundary-spanning or non-local search) is critical in the search for variety, which leads to successful innovation. A representative study is that of Katila and Ahuja (2002) who focus on how firms search or solve problems to create new products. The authors examine whether the number of new products is affected by the degree of search at the firm level in the robotics industry in Europe, Japan, and United States from 1985 to 1996. Using patent data from the United States Patent and Trademark Office, the authors make two search variables: search depth and search scope. Search depth describes repetition from using the same knowledge (i.e., citation of the same patents) associated with exploitative search, whereas, search scope describes the portion of new knowledge citation (i.e., citation of new patents) associated with exploratory search. The authors uniquely hypothesize that search depth and scope increase innovation, but over-searching decreases innovation (i.e., penalty for profit). As a result, the authors find the inverse-U relationship of search depth and innovation, but only a positive relationship of search scope and innovation.

We consider search depth and scope worth analyzing especially when using patent data since citation information is available in patent data. Therefore, following Katila and Ahuja (2002), this study uses search depth and scope variables. Specifically, this study hypothesizes the inverse-U relationship of each search variable.

3. Methodology

3.1 Empirical strategy and variables

This study empirically examines time-period and industry heterogeneity of innovation activity in Japan using the IIP-DB and non-consolidated financial statements obtained from the Nikkei NEEDS database of Nikkei Inc. from 1964 to 2006. Although consolidated data is ideal for capturing innovation activity, it is usually difficult to prepare enough observations of consolidated data before 2000 for Japan. This is because the principle of consolidated financial statements was not fully introduced at Japanese firms until March in 2000.

This study examines the time-period and industry heterogeneity in the regression model, dividing the entire sample into each period (I: 1964-1975; II: 1976-1987; III: 1988-2006) and/or each industry (i.e., manufacturing and non-manufacturing industries). Hence, we estimate 12 specifications (i.e., 3 industries (all, manufacturing, and non-manufacturing industries) multiplied by 4 periods: periods all, I, II, and III).

As a dependent variable proxy for innovation activity, we use registered patents (denoted by *reg*) in applicant year as a proxy for innovation. When using patent measures, empirical studies generally use application patents, registered patents, or citation weighted data (e.g., Aghion et al., 2005; Motohashi, 2011, 2012). Application patents enable earlier access than other variables. In this sense, it is useful to capture the innovation trend. Because an application may be withdrawn, not be requested for examination, or not be registered, however, application patents may be overestimated as a proxy for innovation. From this angle, registered patents are considered a more reasonable proxy for innovation than application patents. On the other hand, these two variables may not appropriately indicate innovation importance or quality. To avoid this problem, the studies sometimes use citation data to weigh each patent value (e.g., Hall et al., 2001). However, the problem associated with citation-weighted patents is that calculation and the methodologies are often complex because of how many things need to be accounted for, such as propensity or obsolescence of patents and technology field (see Hall et al., 2001).

In terms of independent variables in the industrial organization, this study uses total assets (denoted by *assets*) as a proxy for firm size, and HHI as a proxy for market competition. In the innovation literature, traditionally two competition measures, HHI and PCM, are used.[3] HHI is most popular among the two, and it is easy to interpret because missing values are unlikely to occur in definition. One shortcoming, however, is that it requires whole market share, which may be difficult to obtain. In addition, in estimating market share, how to identify the extent of the market may be arbitrary for researchers. On the other hand, PCM is also often used against the theoretical background of the Lerner index. In empirical studies, because price and cost are not usually obtained, the sales-profit ratio is typically used as PCM (e.g., Aghion et al., 2005). However, profit may take a negative value, and therefore, PCM can be negative contrary to the definition. In this sense, PCM measure is often difficult to use in empirical studies.

Regarding search variables, following Katila and Ahuja (2002), we create search variables: depth and scope. In terms of search depth, the authors argue that significant value of the knowledge is lost within approximately five years in high-technology companies, and use repetition within five years as a numerator of the proportion. However, how to determine the reference term (years) is problematic because this study investigates comprehensive industries, including non-manufacturing industries. This is also difficult because the dependent variable in this study is based on the patent measure, as well as search variable. To make it easier to compare other empirical studies, we use repetition within a corresponding single year rather than some previous years. This study defines depth as follows:

$$depth_{it} = repetition\ count_{it} / total\ citations_{it} \tag{1}$$

where i and t denote firm and year, respectively. Similarly, search scope is defined as follows:

$$scope_{it} = new\ citations_{it} / total\ citations_{it} \tag{2}$$

[3] Recently, Boone (2008a, 2008b) proposes relative profits (RP) and relative profit differences (RPD) as an adequate proxy for competition.

In definition, these values range from 0 to 1.[4]

For the hypothesis setting of HHI, *depth*, and *scope*, following Aghion et al. (2005) and Katila and Ahuja (2002), this study hypothesizes a quadratic relationship toward innovation. Therefore, we include linear and quadratic terms of HHI, *depth*, and *scope*, and carefully check whether the relationship is inverse-U, positive, negative, U-shape, or no-significance, as described in the section below.

In addition, a key issue in a regression model is omitted variable bias or endogeneity, possibly leading to loss of consistency. It is, however, generally difficult to specify omitted determinants of the innovation process in the innovation literature. Note that because a regression model of this study is not a set of simultaneous equations or a dynamic model, mutual causality or simultaneity is not an issue in this study. We consider that innovation activity is generally expected to be highly correlated with corporate productivity or profitability. For example, innovation activity should be related to investment situations such as R&D, and it affects corporate business performance. To remove the omitted variable bias as much as possible, we firstly include firm and yearly fixed-effects in the model to control unobserved firm characteristics and yearly macro shocks. In addition, as control variables, we use capital and labor productivity (denoted by *kprod* and *lprod*, respectively) and profit rate (denoted by *profitrate*).

3.2 Regression model

Based on the above discussion, to examine the determinants of innovation activity, this study uses a fixed-effects regression model, controlling unobserved firm fixed-effects with year dummies. As a dependent variable proxy for innovation activity, we use the number of registered patents (*reg*) plus one in the log-form (ln(*reg*+1)). The natural log is used to directly estimate elasticities of determinants. One is added to avoid the natural logarithm of zero. In terms of a scale variable (*asset*), we also take the natural log-form (ln*assets*) to estimate size elasticity.

The model of this study is as follows:

[4] Note that we use citation data of all patent applications rather than that of only registered patents because all citation data will reflect the search characteristics adequately.

$$
\begin{aligned}
\ln(reg_{it}+1) = \beta_0 + \beta_1 \cdot \ln assets_{it} + \beta_2 \cdot HHI_{it} + \gamma_2 \cdot HHI_{it}^2 + \beta_3 \cdot depth_{it} + \gamma_3 \cdot depth_{it}^2 \\
+\beta_4 \cdot scope_{it} + \gamma_4 \cdot scope_{it}^2 + \beta_5 \cdot kprod_{it} + \beta_6 \cdot lprod_{it} + \beta_7 \cdot profitrate_{it} + \beta_i + \beta_t + \varepsilon_{it}
\end{aligned}
\tag{3}
$$

where i and t denote firm i in applicant year t, and ε denotes an error term. This model includes linear and quadratic terms of HHI, *depth*, and *scope*, respectively, to analyze the quadratic effects discussed in the literature.

3.3 Tests for inverse-U effect

In terms of HHI, *depth*, and *scope*, this study carefully checks the effect and statistical significance for coefficients of the linear and quadratic terms. Firstly, using the Wald test, we test joint hypothesis whether the nonlinear (quadratic) effect is statistically significant (i.e., the coefficients of linear and quadratic terms are simultaneously zero).

We next test whether the effect is inverse-U, following Lind and Mehlum (2010). The authors argue that the sufficient condition for inverse-U is that there is only one extreme point of local maximum. The requirement for an inverse-U shape is that a slope of the curve is positive at the start and negative at the end of the interval of each focal variable. In addition to U and inverse-U relationship, this study is further interested in other shapes, positive, negative, or no-significance.

Specifically, this study adopts a following series of null hypotheses to categorize the quadratic relationship. Suppose β and γ denote coefficients of linear and quadratic terms, respectively, and x denotes certain focal variables ranging $[x_l, x_h]$ in a certain regression model. Although Lind and Mehlum (2010) propose two one-sided tests, this study adopts the following two two-sided tests to assess slopes of the curve at start and end as follows:

$$H_0^L : \beta + 2\gamma x_l = 0 \text{ vs. } H_1^L : \beta + 2\gamma x_l \neq 0 \tag{4}$$

$$H_0^H : \beta + 2\gamma x_h = 0 \text{ vs. } H_1^H : \beta + 2\gamma x_h \neq 0 \tag{5}$$

Following the test results, we identify a curve shape, which has five potential types of relationships:

inverse-U, U-shape, positive, negative, and no-significance. As in Lind and Mehlum (2010), inverse-U relationship as a slope of the curve is positive at the start and negative at the end of an interval, whereas U relationship as a slope of the curve is negative at the start and positive at the end of an interval. We further divide the other patterns into positive, negative, and no-significance relationships. A positive relationship is considered slope at the start and/or end is positive at a statistically significant level, whereas a negative relationship is considered slope at the start and/or end is negative at a statistically significant level. In terms of the rest, a no-significance relationship is considered when both slopes of the curve at the start and end are not statistically significant from zero.

In addition, we visually check the shape of quadratic curve and statistical significance in terms of HHI, *depth*, and *scope*. In the model, partial effect of x is represented as $\beta x+\gamma x^2$. On the other hand, in terms of statistical significance, we calculate upper and lower bounds of 95% confidential interval. The interval at α% is calculated as partial effect plus or minus t-value at $(100-\alpha)$% level, multiplied by standard error of partial effect: $\beta x+\gamma x^2 \pm t\sqrt{x^2\cdot \mathrm{var}(\beta)+x^4\cdot \mathrm{var}(\gamma)+2\cdot x\cdot x^2\cdot \mathrm{cov}(\beta,\gamma)}$ (where “var” and “cov” denote variance and covariance of estimators, respectively).

4. Data

The data for this study consists of Japanese firm data and patent data obtained from the Nikkei NEEDS database of Nikkei Inc. and IIP-DB (Goto and Motohashi, 2007). We use the IIP-DB published on March 30 in 2011 (i.e., iipdb20110330). The database includes patent application data, patent registration data, applicant data, rights holder data, citation information, and inventor data.

To merge financial data (Nikkei NEEDS) and patent data (IIP-DB), we used the applicant list of the IIP-DB as in Motohashi (2011, 2012). In the Japanese patent system, similar to the Leahy-Smith America Invents Act amended in 2011 in the U.S., inventors and applicants do not have to match. Investors are persons and can be applicants at the beginning, and applicants (which may be artificial persons) are potential patentees. In most cases, when an employee invention is made in a certain company, although the inventing staff is an investor, the company becomes an applicant.

Specifically, we first match the firm data with a patent applicant list from the IIP-DB. We then cover changes in business names and head office addresses for all of the samples from investor relations and financial reports, among others. Consequently, we match the business names with the applicant name found in a database. Some characters in the list are occasionally wrong, probably due to the degree of accuracy of optical character recognition. Hence, we re-check the matched list for errors.

Table 1 presents the descriptive statistics of data. Figure 1 shows scatter plots of the entire sample in terms of firm size (total assets), competition (HHI), and search variables (*depth* and *scope*) toward raw registered patents at the firm and industry-average levels. The entire sample has 94,108 firm-level observations (where the net number of firms is 3,449) from 1964 to 2006, and the observations in period I (1964-1975), II (1976-1987), and III (1988-2006) are 17,909, 24,897, and 51,302, respectively.

This study uses large industry classification (manufacturing and non-manufacturing industries) based on a three-digit industry classification of Nikkei NEEDS database (see Appendix Table 1). Manufacturing industries (observations: 54,761) consist of the following 17 industries: food, textile, pulp and paper, chemical, pharmaceutical products, petroleum, rubber, ceramic, iron and steel, non-ferrous metal, machinery, electric machinery, shipbuilding, automobile, other transport equipment, precision machinery, and other. On the other hand, non-manufacturing industry (observations: 39,347) consists of the following 16 industries: fishery, mining, building, trading interests, retail, other financial industry, estate, rail and bus service, land transportation, marine transportation, air transportation, warehousing and allied transportation, communication, electric utility, gas utility, and other service.

HHI in this study is calculated by using sales share in the entire sample for each year for each small industry classification (17 manufacturing and 16 non-manufacturing industries). Observation for HHI estimation is 95,081, and larger than the observation for the regression model because there are missing values related to financial data, except for sales (see Appendix Table A1).

In terms of control variables, we consider value added as business economic values of firms, and calculate value added as earnings before interest, taxes, depreciation, and amortization (EBITDA), plus labor costs[5]. Using fixed assets (million yen) and employee numbers (person) as capital and labor factors, respectively, this study calculates capital and labor productivities (*kprod* and *lprod*) as value added divided by each of capital and labor factors in the natural log-form as follows:

$$kprod_{it} = \ln\left(value\ added_{it} / fixed\ assets_{it}\right) \tag{6}$$

$$lprod_{it} = \ln\left(value\ added_{it} / employee\ number_{it}\right) \tag{7}$$

where i and t denote firm and year, respectively. On the other hand, profitability is often calculated as profit divided by business economic value. Using earnings before interest and taxes (EBIT) as profit, this study defines profitability (*profitrate*) as follows:

$$profitrate_{it} = EBIT_{it} / value\ added_{it}\ . \tag{8}$$

Profitrate reflects how much companies can retain from value added. Note that because EBIT takes a negative value in our dataset, *profitrate* also takes negative value.

5. Results

Table 2 shows the regression result. In terms of time heterogeneity, the estimated observations are for all periods in columns 1, 2, and 3, the period I (1964-1975) in columns 4, 5, and 6, the period II (1976-1987) in columns 7, 8, and 9, and the period III (1976-1987) in columns 10, 11, and 12. In terms of industry heterogeneity, the estimate observations are all industries in columns 1, 4, 7, and 10, manufacturing industries in columns 2, 5, 8, and 11, and non-manufacturing industries

[5] Labor cost is calculated by sum of the following variables in Nikkei NEEDS database: 1) operating labor cost and allied welfare cost; 2) labor cost for sales and marketing and allied welfare cost; 3) board members' compensation and employee bonus. Note that these three variables are ambiguous among firms and may take missing values. Therefore, this study substitutes zero value for missing values.

in columns 3, 6, 9, and 12.

The middle part of table shows the result of the joint test (Wald test) for linear and quadratic terms of HHI, *depth*, and *scope*, respectively (where each value denotes F-value). The lower part of the table shows the result of the slope test at the start and end of each interval: HHI, *depth*, and *scope*. Each value denotes slope at minimum and maximum of the interval. Following the slope tests of both sides, "Pos", "Neg", and "invU" denote positive, negative, and inverse-U relationship of each curve, respectively. Figures 2, 3, and 4 show partial effects of HHI, *depth*, and *scope*, respectively. The lines denote the estimated partial effect ($\beta x+\gamma x^2$), and the dashed lines denote upper and lower bounds of 95% confidential interval. Appendix Figures A1, A2, and A3 show scatter plots of HHI, *depth*, and *scope*, respectively, toward ln(*reg*+1).

5.1 Size

In terms of size elasticity, the coefficient of ln*assets* is statistically significantly different from zero and positive in all specifications except for the non-manufacturing industries in period II (#9 in Table 2). In all industries in all periods (#1), the elasticity is 0.223.

When considering time heterogeneity in all industries, the elasticities are 0.144, 0.114, and 0.137 in the periods I, II, and III, respectively (#4, 7, and 10). This indicates that the elasticities are similar among each period (between 0.114 and 0.144), but are lower than the entire period (0.223).

On the other hand, when considering industry heterogeneity, the elasticity in all periods is 0.434 in the manufacturing industries (#2) (0.242, 0.232, and 0.296 in the periods I, II, and III, respectively, in #5, 8, and 11), and 0.065 in the non-manufacturing industries (#3) (0.048 and 0.053 in the periods I and III, respectively, in #6 and 12; non-significance in the period II in #9). This indicates that firm size is much more important for innovation in the manufacturing industries than the non-manufacturing industries. This also indicates that the elasticities are similar among each period, but become smallest in the period II (#7, 8, and 9).

5.2 Market competition

In terms of market competition (HHI), the joint test for HHI and HHI^2 shows that the effect of HHI is statistically significant in all industries in all periods in I, II, and III (#1, 4, 7, and 10), and non-manufacturing industries in period III (#12). Among these, the slope test of HHI shows that the effect is inverse-U in all industries in periods all, I, and II (#1, 4, and 7), and negative in all and non-manufacturing industries in period III (#10 and 12).

Based on the result, inverse-U effect of HHI is shown in all industries in all periods (#1) as in Aghion et al. (2005). The extremum point of HHI is 0.419.

When considering industry heterogeneity, the effect is not significant in manufacturing and non-manufacturing industries (#2 and 3). Note that the effect in manufacturing industries in all periods (#2) is inverse-U, but not significant in the joint test. This result will illustrate how fragile the relationship between competition and innovation is in the literature. In a technical sense, there may be two reasons for this. One is that industrial classifications are often not appropriate for actual business boundaries. Another explanation is that competition variables are likely to be rough because they are often observed at industry or sector levels, not at firm or business establishment levels. Indeed, HHI in this study is observed at intervals (see Appendix Figure A1). These issues may make the relationship between competition and innovation unclear.

We then check time-period heterogeneity. In all industries, the effect shifts from inverse-U in periods I and II (#4 and 7) to negative in period III (#10). Specifically, the extremum point moves from 0.603 in period I (#4) to 0.417 in period II (#7). In period III (#3), because of the negative relationship, the highest effect occurs where HHI is equal to zero. This may indicate a kind of structural break, as in Correa (2012). It suggests that as the degree of patent protection (appropriability) intensifies, the innovation rate is encouraged by more competition (i.e., positive relationship in the literature).

5.3 Search depth

In terms of *depth*, the joint test shows that the effect of *depth* is statistically significantly different from zero in all specifications. On the other hand, the slope test (u-test) denotes that the effect is inverse-U in all specifications. This result is in line with Katila and Ahuja (2002).

When considering time-period heterogeneity, the inverse-U shape is almost the same among the periods, but the extremum point in the period III is larger than that of the other two periods. In all industries (#1, 4, 7, and 10), the extremum points are 0.212 in all periods, 0.203 in period I, 0.208 in period II, and 0.283 in period III.

On the other hand, when considering industry heterogeneity, the extremum point in the manufacturing industries is smaller than in the non-manufacturing industries. The extremum points are 0.201 in the manufacturing industries in all periods (#2) (0.195, 0.190, and 0.251 in periods I, II, and III, respectively, in #5, 8, and 11), and 0.244 in non-manufacturing industries in all periods (#3) (0.335, 0.300, and 0.298 in the periods I, II, and III, respectively, in #6, 9, and 12). This indicates that *depth* is required more in non-manufacturing industries than manufacturing industries.

One of key characteristics of this result is that the penalty for innovation is strict (see Figure 3). As *depth* grows from zero to one, the innovation rate increases, peaks, decreases, and then gets lower than the start point (i.e., where *depth* is more than two times higher than the extremum point; e.g., approximately 0.4-0.6).

5.4 Search scope

In terms of *scope*, the joint test shows that effect of *scope* is statistically significantly different from zero in all specifications. On the other hand, the slope test shows that the effect of *scope* is inverse-U in all specifications except for the non-manufacturing industries in period I (#6). In #6, a non-significance relationship is found. This result basically supports the inverse-U relationship unlike that of Katila and Ahuja (2002), who show a positive relationship between *scope* and innovation.

In terms of time heterogeneity, the inverse-U shape is almost the same among the periods. The extremum points in all industries are 0.609, 0.662, 0.619, and 0.685 in all periods, I, II, and III, respectively (#1, 4, 7, and 10).

On the other hand, in terms of industry heterogeneity, the extremum point of inverse-U in manufacturing industries is larger than in non-manufacturing industries. The extremum points of inverse-U are 0.630 in the manufacturing industries in all periods (#2) (0.657, 0.625, and 0.700 in the periods I, II, and III, respectively, in #5, 8, and 11), and 0.573 in the non-manufacturing industries in all periods (#3) (0.624 and 0.603 in the periods II and III, respectively; non-significance in period I). The opposite of *depth,* this indicates that *scope* is more required in manufacturing industries than non-manufacturing industries.

In addition, compared to *depth*, the penalty of over-searching for *scope* is more modest than *depth* (see Figures 3 and 4). As *scope* gets large from zero to one, the innovation rate increases, peaks, and decreases. It does not, however, get lower than the starting point; therefore, the innovation rate is lowest where *scope* is 0.

5.5 Control variables

In terms of control variables, the coefficient of capital productivity (*kprod*) is statistically significantly different from zero and positive in 8 specifications (#1, 2, 3, 4, 5, 10, 11, and 12). The coefficient of labor productivity (*lprod*) is statistically significantly different from zero and negative in 8 specifications (#1, 2, 3, 4, 5, 10, 11, and 12). The coefficient of profitability (*profitrate*) is statistically significantly negative in 2 specifications (#4 and 5).

While the result is not always robust, it shows that capital and labor productivities tend to be associated positively and negatively with innovation rate, respectively. This indicates that firms with less capital and more employees are more likely to be innovative in Japan. In addition, although some specifications show a negative relationship, profit rate is not likely to be correlated to innovation rate.

In terms of industry heterogeneity in all industries (#2 and 3), the elasticities of capital productivity are 0.125 and 0.033 in manufacturing and non-manufacturing industries, respectively. On the other hand, the elasticities of labor productivity are −0.095 and −0.048 in manufacturing and non-manufacturing industries, respectively. Therefore, absolute values of the elasticities in manufacturing industries are larger than in non-manufacturing industries. This indicates that capital or labor conditions are more important in promoting innovation in manufacturing industries than in non-manufacturing industries.

6. Conclusions

This study examines time-period and industry heterogeneity of innovation activity in Japan from 1964 to 2006 using patent data and non-consolidated firm data. In terms of time-period heterogeneity, this study focuses on the following three periods based on changes in the Japanese patent system: I) before 1976; II) 1976–1987; and III) after 1988. On the other hand, in terms of industry heterogeneity, this study examines both manufacturing and non-manufacturing industries. Specifically, in each degree of patent protection in each industry, this study focuses on the following popular determinants in the literature: size, market competition, and search variety (depth and scope).

In terms of size effect (ln*assets*), the elasticity value is 0.223 in the entire sample. This indicates that a 1% increase in size is associated with a 0.223% increase in innovation rate. The positive less-than-one value is often estimated in the innovation literature (Cohen and Levin, 1989; Gilbert, 2006; Cohen, 2010). In terms of time-period heterogeneity, the elasticities are similar among the three periods (between 0.114 and 0.144); however, they are lower than the entire period. This implies that using too-long time series data may lead to over- or under-estimating the size elasticity. On the other hand, in terms of industry heterogeneity, the elasticities in the entire period are 0.434 and 0.065 in manufacturing and non-manufacturing industries, respectively. This suggests that the manufacturing industry in Japan enjoys larger economies of scale for innovation than does the non-manufacturing industry.

In terms of market competition, the effect of HHI in the entire sample is inverse-U, as in Aghion et al. (2005) and Inui et al. (2012). However, the inverse-U effect is not stable, as argued in the innovation literature, when considering time-period and industry heterogeneity. In terms of time-period heterogeneity, the effect of HHI in the entire industries significantly changes from inverse-U in periods I and II to a positive relationship in period III (i.e., opposite to the Schumpeterian hypothesis). In terms of industry heterogeneity, on the other hand, the effect in the entire period is not significant in either the manufacturing and non-manufacturing industries.

The result of HHI will illustrate how fragile the relationship between competition and innovation is in the literature. In the technical sense, there may be two reasons for this fragility. One is that industrial classifications often are not appropriate for actual business boundaries. Another is that competition variables are likely to be rough because they are often observed at industry or sector levels, not at firm or business establishment levels. However, if these technical issues are not problematic, the result implies that empirical analysis, which simply uses competition and innovation variables as independent and dependent variables, respectively, do not considerably contribute to the Schumpeterian hypothesis. This is because the empirical relationship between competition and innovation tends to rely largely on time-period or industry heterogeneity of the sample.

In terms of search variety, the effects of *depth* and *scope* are significant and inverse-U in almost all specifications. This result partially supports Katila and Ahuja (2002), who show *depth* has an inverse-U effect whereas *scope* has a positive effect. In terms of time-period heterogeneity, the shape of the effect is almost same. On the other hand, in terms of industry heterogeneity, the peaks of inverse-U effect (the extremum points) are slightly different between the manufacturing and non-manufacturing industries. In the entire period, the extremum point of *depth* in manufacturing industries is smaller than in non-manufacturing industries. It is the opposite, however, in the case of *scope*. This suggests that in innovation activity, manufacturing industries tend to require less exploitative search (or local search) and more exploratory search (boundary-spanning or non-local search) than do non-manufacturing industries. This may not be intuitive, but it implies that non-manufacturing industries prefer R&D that generates profits more effectively (i.e., more exploitative search) and certainly (i.e., less exploratory search).

As the overall tendency of innovation activities in Japan, time-period heterogeneity is small among size and search variety. This suggests that the degree of patent protection (i.e., appropriability condition) does not considerably change effects of these determinants. On the other hand, industry heterogeneity is relatively large among size, market competition, and search variety. Therefore, in empirical studies, industry heterogeneity, rather than time-period heterogeneity, should be considered.

A remarkable case is market competition. The effect of market competition is not stable as argued in the innovation literature both, in terms of time-period and industry heterogeneity. Thus, future research may be necessary to compare results using other competition measures such as PCM or those as in Boone (2008a, 2008b). However, in light of the many inconclusive results in the literature, the empirical strategy or focus may need further consideration. As shown in this study, empirical results are often not robust when using proxy variables of competition and innovation at firm level.

As remaining issues, this study finds that the effect of search variety is different from Katila and Ahuja (2002), but the effect is relatively robust in terms of industry and time-period heterogeneity argued in the evolutionary economics literature (Laursen, 2012). Therefore, in future research, it is also worth examining other topics in Laursen (2012) such as geographical issues, organizational designs and slacks, and “variety paradox” (Patel and Pavitt 1997). As shown in this study, industry heterogeneity will be important, making the further identification of industry heterogeneity a worthwhile endeavor.

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Table 1 descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
reg	94,108	25.984	155.330	0	5397
ln(*reg*+1)	94,108	1.155	1.621	0	8.594
HHI	94,108	0.065	0.061	0.017	1.000
depth	94,108	0.032	0.078	0	0.909
scope	94,108	0.399	0.454	0	1.000
kprod	94,108	−0.454	0.777	−9.179	4.510
lprod	94,108	2.025	0.945	−4.985	9.057
profitrate	94,108	0.242	2.489	−491.493	1.000
ln*assets*	94,108	10.204	1.628	0.693	16.476

Table 2 Regression result

#	1	2	3	4	5	6
Period	All	All	All	I (64-75)	I (64-75)	I (64-75)
Industry	All	Man.	Non.	All	Man.	Non.
ln*assets*	0.223***	0.434***	0.065***	0.144***	0.242***	0.048***
	(0.013)	(0.022)	(0.009)	(0.020)	(0.034)	(0.017)
HHI	1.904***	1.880*	0.228	1.802***	2.408*	0.701
	(0.376)	(1.039)	(0.246)	(0.536)	(1.317)	(0.448)
HHI^2	−2.270***	−3.193*	−0.478	−1.493***	−3.987	−0.616
	(0.508)	(1.674)	(0.358)	(0.555)	(3.207)	(0.378)
depth	3.269***	3.469***	2.861***	1.334**	1.032*	11.867*
	(0.224)	(0.246)	(0.507)	(0.548)	(0.539)	(6.911)
$depth^2$	−7.701***	−8.628***	−5.862***	−3.279***	−2.640***	−17.707**
	(0.518)	(0.632)	(0.892)	(0.940)	(0.917)	(7.488)
scope	4.524***	4.091***	5.049***	2.532***	2.426***	−2.931
	(0.165)	(0.164)	(0.427)	(0.411)	(0.412)	(6.564)
$scope^2$	−3.717***	−3.249***	−4.403***	−1.913***	−1.847***	3.683
	(0.163)	(0.160)	(0.423)	(0.408)	(0.410)	(6.555)
kprod	0.068***	0.125***	0.033***	0.044**	0.082**	0.003
	(0.011)	(0.019)	(0.009)	(0.022)	(0.035)	(0.018)
lprod	−0.074***	−0.095***	−0.048***	−0.058**	−0.102**	−0.024
	(0.014)	(0.023)	(0.014)	(0.025)	(0.040)	(0.023)
profitrate	−0.000	−0.002	−0.0004	−0.001***	−0.001**	0.001
	(0.001)	(0.002)	(0.001)	(0.000)	(0.000)	(0.002)
constant	−1.549***	−2.903***	−0.615***	−0.788***	−1.383***	−0.423***
	(0.117)	(0.194)	(0.090)	(0.176)	(0.292)	(0.157)
Firm effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
obs	94,108	54,761	39,347	17,909	12,307	5,602
net # of firms	3,449	1,693	1,756	1,781	1,200	581
within R squared	0.468	0.508	0.449	0.271	0.275	0.311
between R squared	0.706	0.777	0.747	0.580	0.677	0.494
overall R squared	0.635	0.698	0.626	0.469	0.573	0.395
joint test (Wald test)						
HHI, HHI^2	12.81***	1.83	0.9	7.07***	2.15	1.33
depth, $depth^2$	115.1***	101.94***	21.76***	7.08***	5.00***	6.41***
scope, $scope^2$	1942.44***	1194.77***	630.63***	355.54***	272.46***	74.36***
slope test of HHI						
slope at min	1.829***	1.775*	0.212	1.753***	2.276*	0.680
slope at max	−2.634***	−4.503*	−0.728	−1.183*	−5.562	−0.532
result	invU	invU	—	invU	Pos	—
slope test of depth						
slope at min	3.269***	3.469***	2.861***	1.334**	1.032*	11.867*
slope at max	−10.732***	−12.218***	−7.798***	−4.628***	−3.768***	−20.327***
result	invU	invU	invU	invU	invU	invU
slope test of scope						
slope at min	4.524***	4.091***	5.049***	2.532***	2.426***	−2.931
slope at max	−2.909***	−2.406***	−3.757***	−1.295***	−1.269***	4.435
result	invU	invU	invU	invU	invU	—

Notes: (1) The upper part of table shows the result of a fixed-effects regression model. In each column, All, Man, and Non denote the entire, manufacturing, and non-manufacturing industries, respectively. The dependent variable is ln(reg+1). ***, **, * denote statistical significances at the 1%, 5%, and 10% level, respectively. Coefficients are without parentheses, whereas cluster robust standard errors (clustered by firm) are in parentheses. (2) The middle part of table shows the result of joint test (Wald test) for linear and quadratic terms of HHI, depth, and scope, respectively. Each value denotes F-value, and *** and * denotes statistical significances at the 1% and 10% level. (3) The lower part of table shows the result of slope test at the start and end of each interval: HHI, depth, and scope. Each value denotes slope at minimum and maximum of the interval. ***, **, * denote statistical significances at the 1%, 5%, and 10% level of two-sided t-test, respectively. “Pos”, “Neg”, and “invU” denote positive, negative, and inverse-U relationship of each curve, respectively.

Table 2 Regression result (cont.)

#	7	8	9	10	11	12
Period	II (76-87)	II (76-87)	II (76-87)	III (88-06)	III (88-06)	III (88-06)
Industry	All	Man.	Non.	All	Man.	Non.
ln*assets*	0.114***	0.232***	0.002	0.137***	0.296***	0.053***
	(0.020)	(0.033)	(0.013)	(0.010)	(0.025)	(0.008)
HHI	1.257***	0.335	0.092	−1.062*	2.411*	−2.268***
	(0.420)	(1.210)	(0.279)	(0.563)	(1.246)	(0.650)
HHI^2	−1.506***	−2.429	−0.124	0.198	−3.740*	1.642***
	(0.490)	(2.104)	(0.359)	(0.725)	(2.237)	(0.600)
depth	2.073***	1.954***	2.842***	2.968***	3.261***	1.442***
	(0.254)	(0.263)	(0.731)	(0.188)	(0.226)	(0.341)
$depth^2$	−4.994***	−5.143***	−4.738***	−5.237***	−6.497***	−2.420***
	(0.553)	(0.576)	(1.316)	(0.420)	(0.585)	(0.566)
scope	3.137***	3.115***	2.555***	2.212***	2.426***	2.839***
	(0.186)	(0.196)	(0.556)	(0.136)	(0.150)	(0.308)
$scope^2$	−2.534***	−2.493***	−2.047***	−1.614***	−1.733***	−2.355***
	(0.182)	(0.191)	(0.553)	(0.132)	(0.142)	(0.307)
kprod	−0.015	−0.011	0.007	0.074***	0.147***	0.023***
	(0.018)	(0.029)	(0.014)	(0.011)	(0.020)	(0.008)
lprod	0.001	−0.011	−0.003	−0.071***	−0.121***	−0.021*
	(0.021)	(0.036)	(0.017)	(0.013)	(0.024)	(0.012)
profitrate	0.002	0.010	−0.001	−0.000	−0.002	−0.000
	(0.002)	(0.010)	(0.001)	(0.001)	(0.002)	(0.000)
constant	−0.301	−0.979***	0.137	−0.344***	−2.410***	−0.126*
	(0.199)	(0.320)	(0.136)	(0.097)	(0.268)	(0.071)
Firm effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
obs	24,897	15,486	9,411	51,302	26,968	24,334
net # of firms	2,371	1,416	955	3,311	1,589	1,722
within R squared	0.294	0.311	0.291	0.268	0.327	0.254
between R squared	0.800	0.818	0.818	0.741	0.765	0.641
overall R squared	0.676	0.715	0.626	0.655	0.684	0.552
joint test (Wald test)						
HHI, HHI^2	4.77***	1.42	0.06	2.76*	1.88	6.38***
depth, $depth^2$	41.00***	40.15***	7.62***	130.65***	112.16***	9.58***
scope, $scope^2$	681.61***	477.26***	182.04***	1152.73***	604.59***	583.05***
slope test of HHI						
slope at min	1.207***	0.255	0.088	−1.055*	2.287*	−2.213***
slope at max	−1.754***	−4.521	−0.156	−0.665	−5.066	1.014
result	invU	—	—	Neg	Pos	Neg
slope test of depth						
slope at min	2.073***	1.954***	2.842***	2.968***	3.261***	1.442***
slope at max	−7.007***	−7.396***	−5.772***	−6.553***	−8.553***	−2.958***
result	invU	invU	invU	invU	invU	invU
slope test of scope						
slope at min	3.137***	3.115***	2.555***	2.212***	2.426***	2.839***
slope at max	−1.931***	−1.871***	−1.540***	−1.016***	−1.041***	−1.871***
result	invU	invU	invU	invU	invU	invU

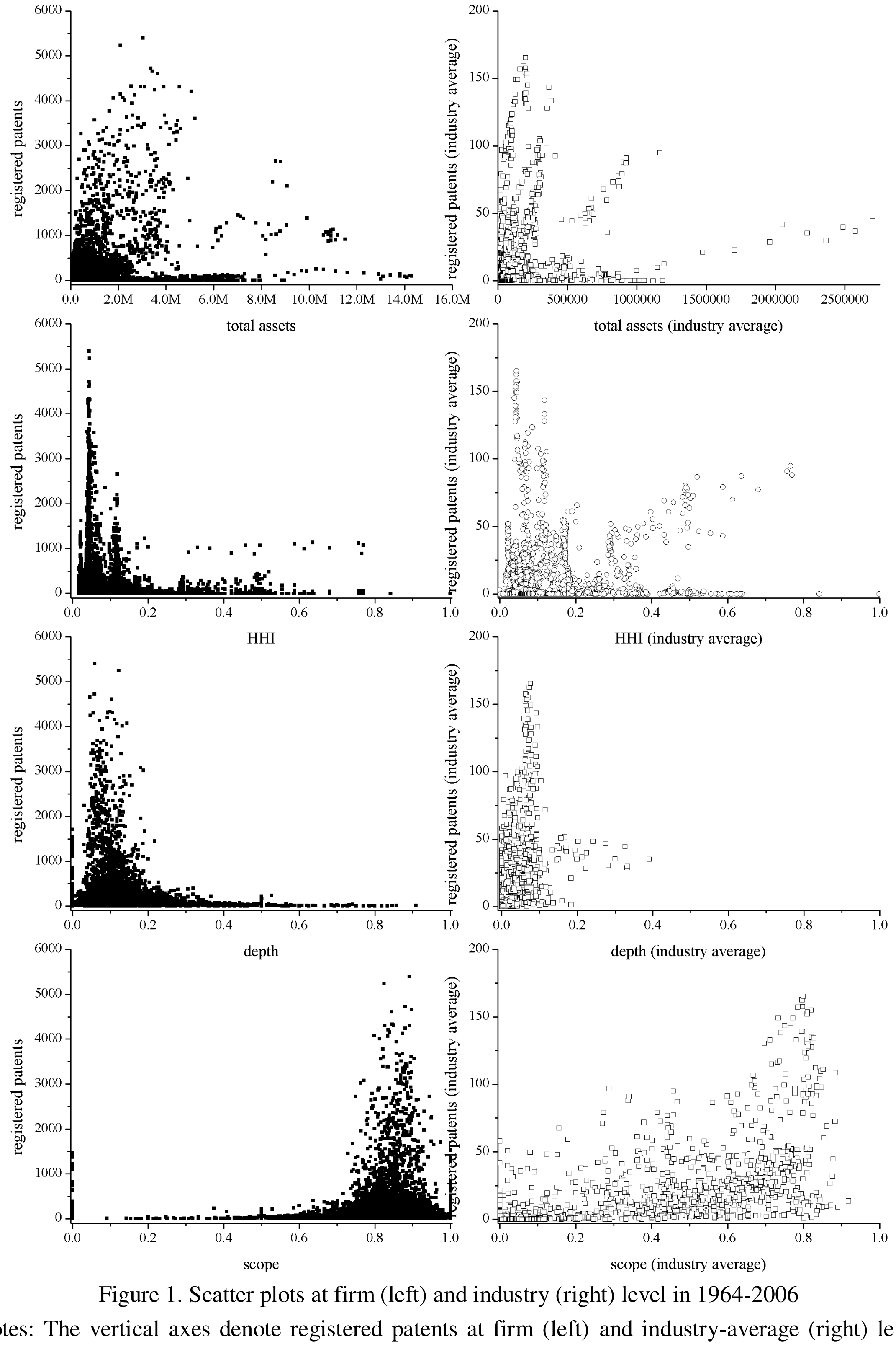


Figure 1. Scatter plots at firm (left) and industry (right) level in 1964-2006

Notes: The vertical axes denote registered patents at firm (left) and industry-average (right) level where industry-average is based on 33 industries of small industry classification. From the top down, the horizontal axes denote total assets (million yen), HHI, depth, and scope, respectively.

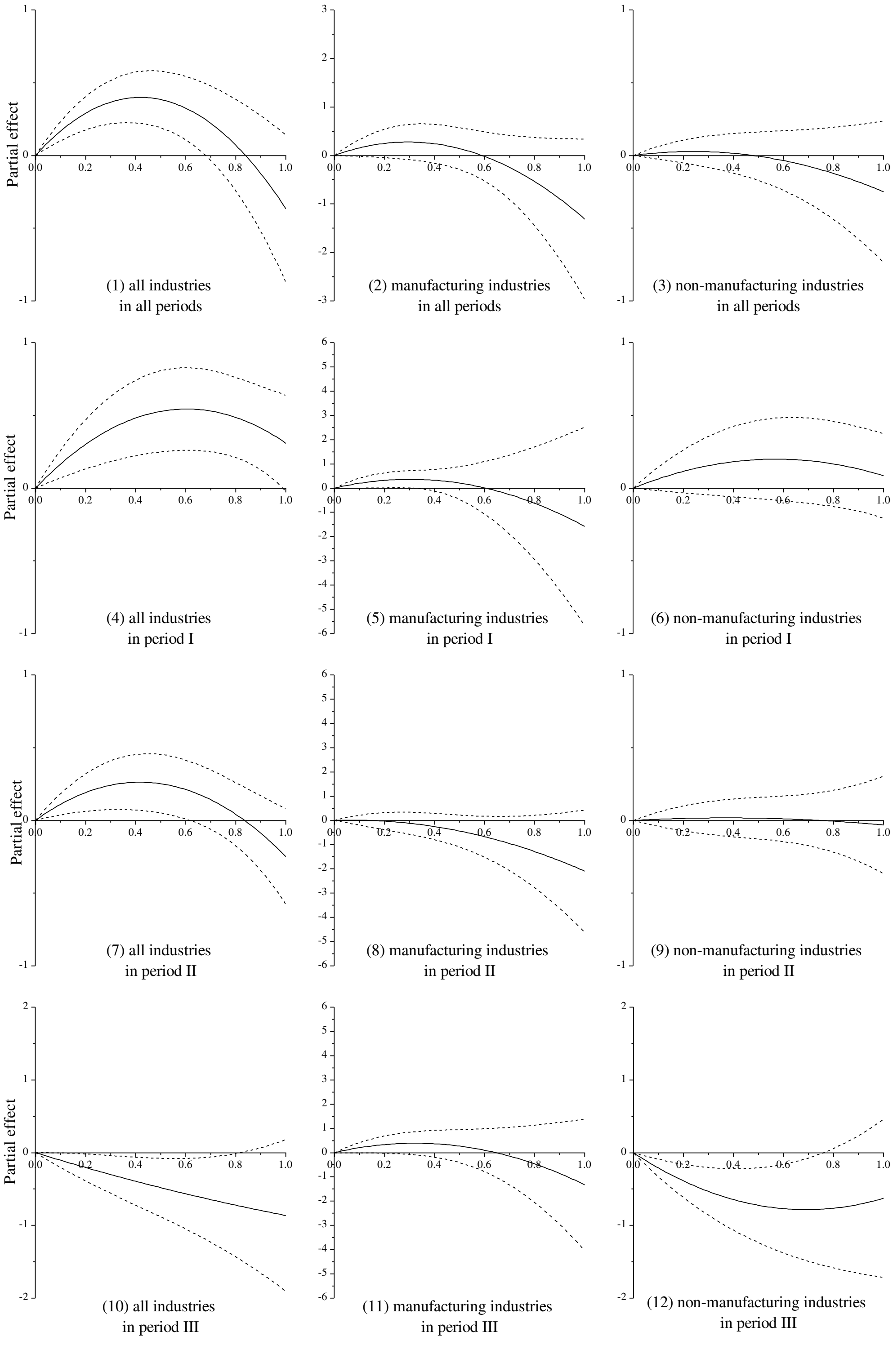


Figure 2. Partial effect of HHI

Notes: The horizontal and vertical axes denote HHI and its partial effect, respectively, in Table 2. The line denotes estimated effect, and the dashed lines denote the upper and lower bounds of 95% confidential interval, respectively. Each figure numbers correspond to the column numbers of Table 2.

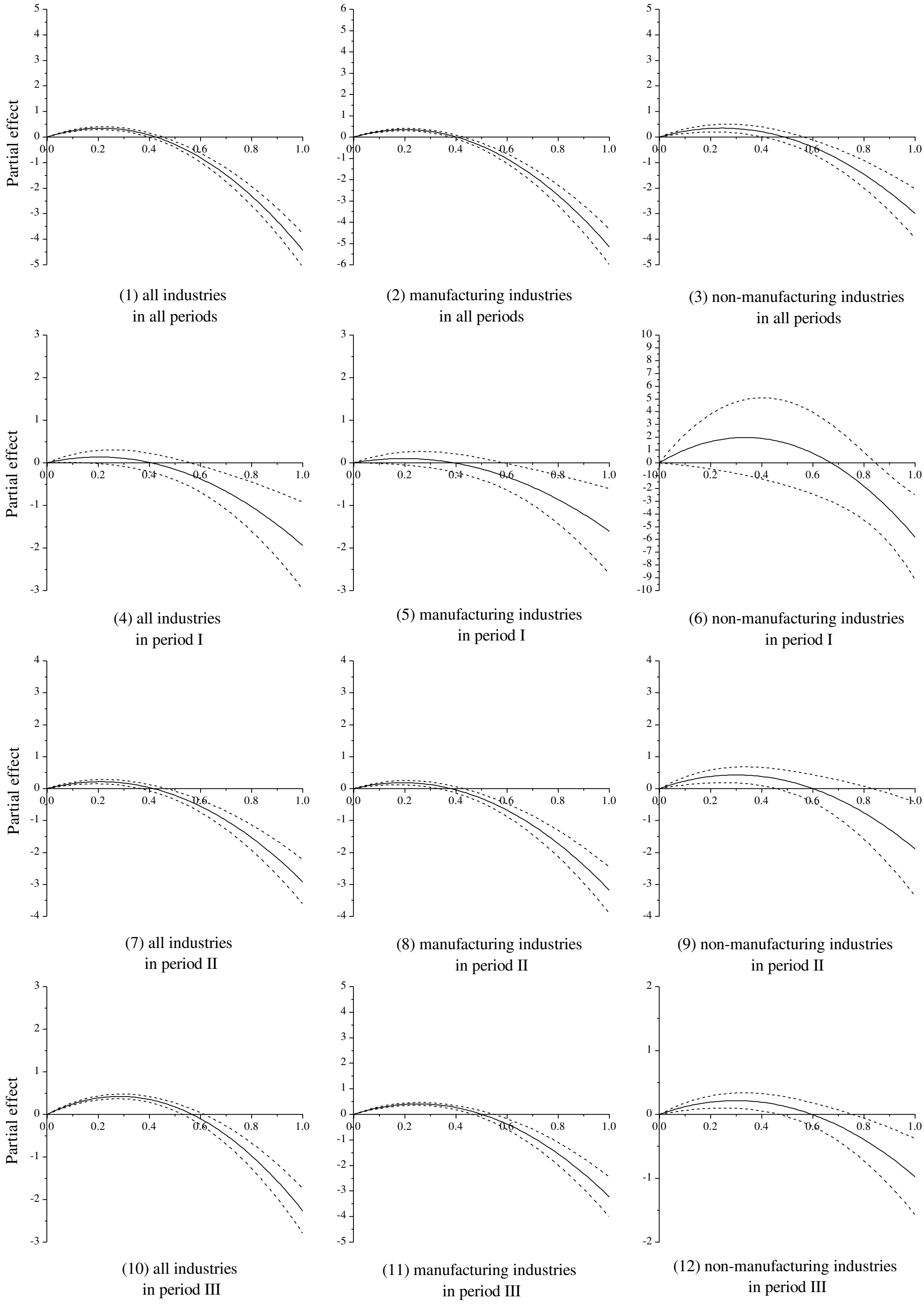


Figure 3. Partial effect of depth

Notes: The horizontal and vertical axes denote depth and its partial effect, respectively, in Table 2. The line denotes estimated effect, and the dashed lines denote upper and lower bounds of 95% confidential interval, respectively. Each figure numbers correspond to the column numbers of Table 2.

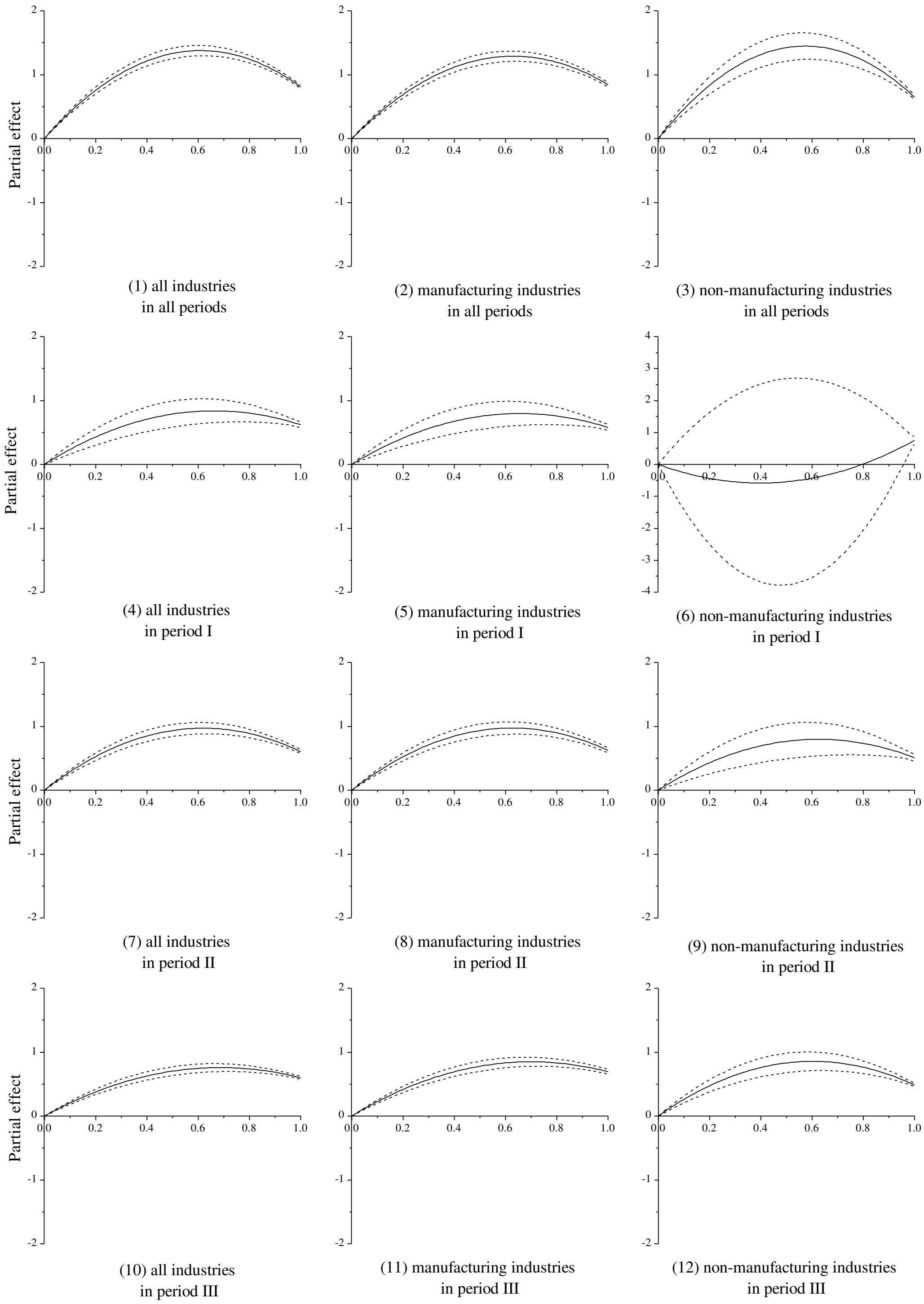


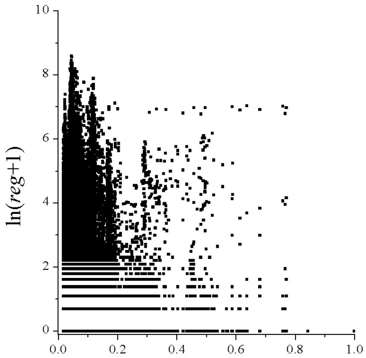
Figure 4. Partial effect of scope

Notes: The horizontal and vertical axes denote scope and its partial effect, respectively, in Table 2. The line denotes estimated effect, and the dashed lines denote upper and lower bounds of 95% confidential interval, respectively. Each figure numbers correspond to the column numbers of Table 2.

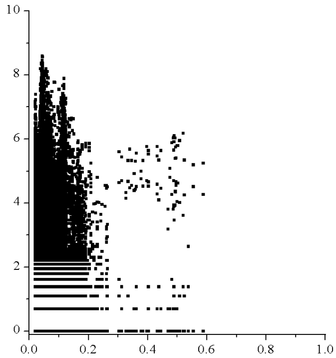
Appendix

Appendix Table A1. Industry classification and observations

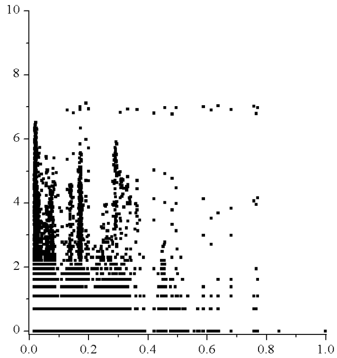
#	Industry	for regression obs	for regression (net # of firms)	for HHI estimation obs	for HHI estimation (net # of firms)
	Large industry classification				
	Manufacturing industry	54,761	1,693	55,027	1,697
	Non-manufacturing industry	39,347	1,756	40,054	1,783
	Manufacturing industries				
1	food	4,750	153	4,781	153
2	textile	3,031	88	3,051	88
3	pulp and paper	1,416	42	1,425	43
4	chemical	6,944	204	6,952	205
5	pharmaceutical products	1,840	56	1,853	57
6	petroleum	533	16	535	16
7	rubber	880	25	881	25
8	ceramic	2,595	78	2,600	78
9	iron and steel	2,509	72	2,516	72
10	non-ferrous metal	4,585	144	4,603	145
11	machinery	8,386	252	8,414	252
12	electric machinery	8,785	284	8,872	284
13	shipbuilding	280	11	285	11
14	automobile	2,836	81	2,836	81
15	other transport equipments	805	27	809	27
16	precision machinery	1,707	54	1,720	54
17	other manufacturing industries	2,879	106	2,894	106
	Non-manufacturing industries				
18	fishery	276	9	280	9
19	mining	474	15	477	15
20	building	7,124	222	7,154	222
21	trading interests	9,315	364	9,361	365
22	retail	4,811	231	4,846	232
23	other financial industry	1,293	64	1,405	85
24	estate	1,989	99	2,068	100
25	rail and bus service	1,294	34	1,294	34
26	land transportation	893	31	895	31
27	marine transportation	1,003	27	1,016	27
28	air transportation	221	7	224	7
29	warehousing and allied transportation	1,450	42	1,450	42
30	communication	570	32	592	32
31	electric utility	441	11	441	11
32	gas utility	463	13	463	13
33	other service	7,730	555	8,088	558
	Total	94,108	3,449	95,081	3,480



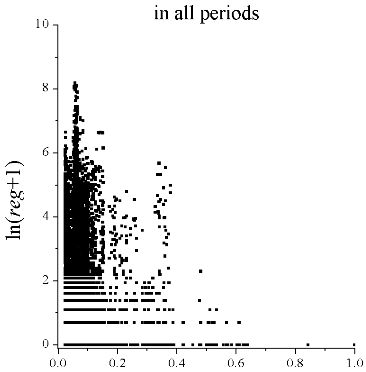
(1) all industries
in all periods



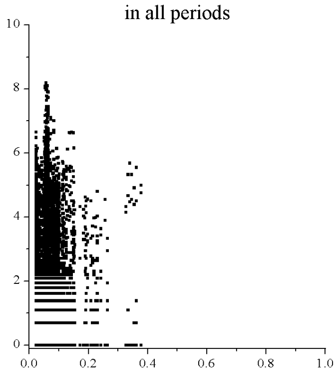
(2) manufacturing industries
in all periods



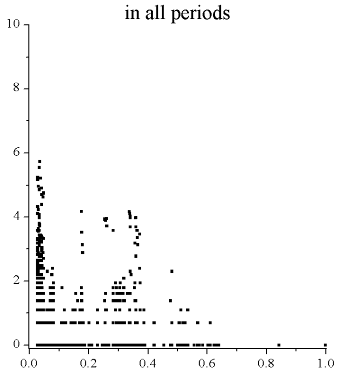
(3) non-manufacturing industries
in all periods



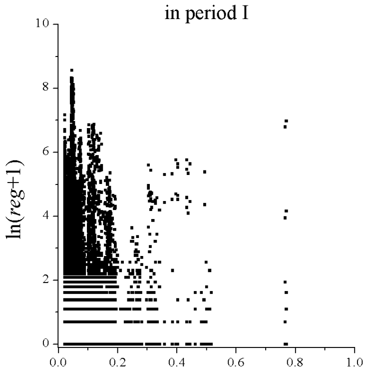
(4) all industries
in period I



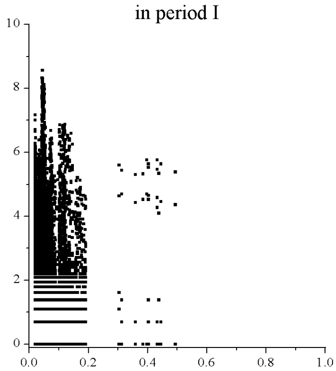
(5) manufacturing industries
in period I



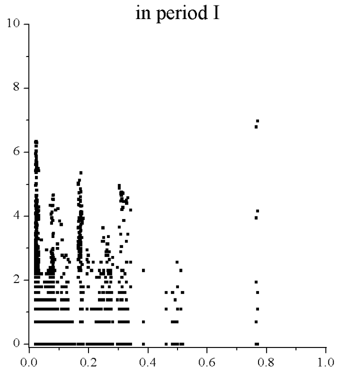
(6) non-manufacturing industries
in period I



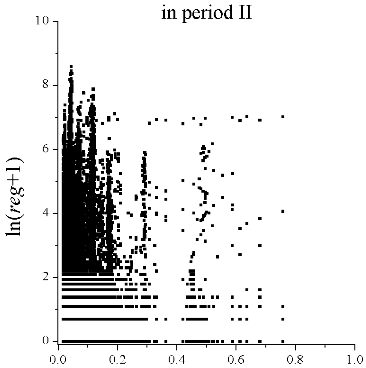
(7) all industries
in period II



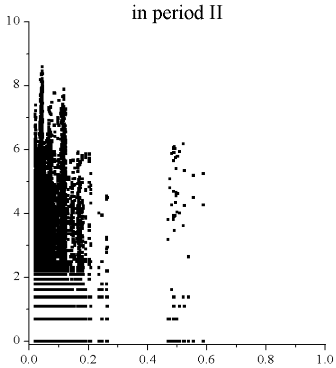
(8) manufacturing industries
in period II



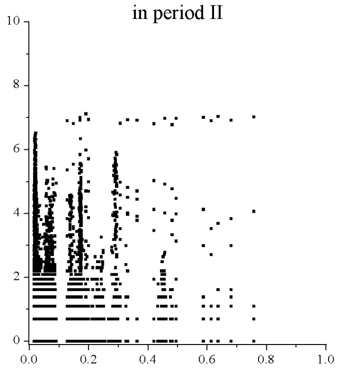
(9) non-manufacturing industries
in period II



(10) all industries
in period III



(11) manufacturing industries
in period III



(12) non-manufacturing industries
in period III

Figure A1. Scatter plot of HHI toward ln(*reg*+1)

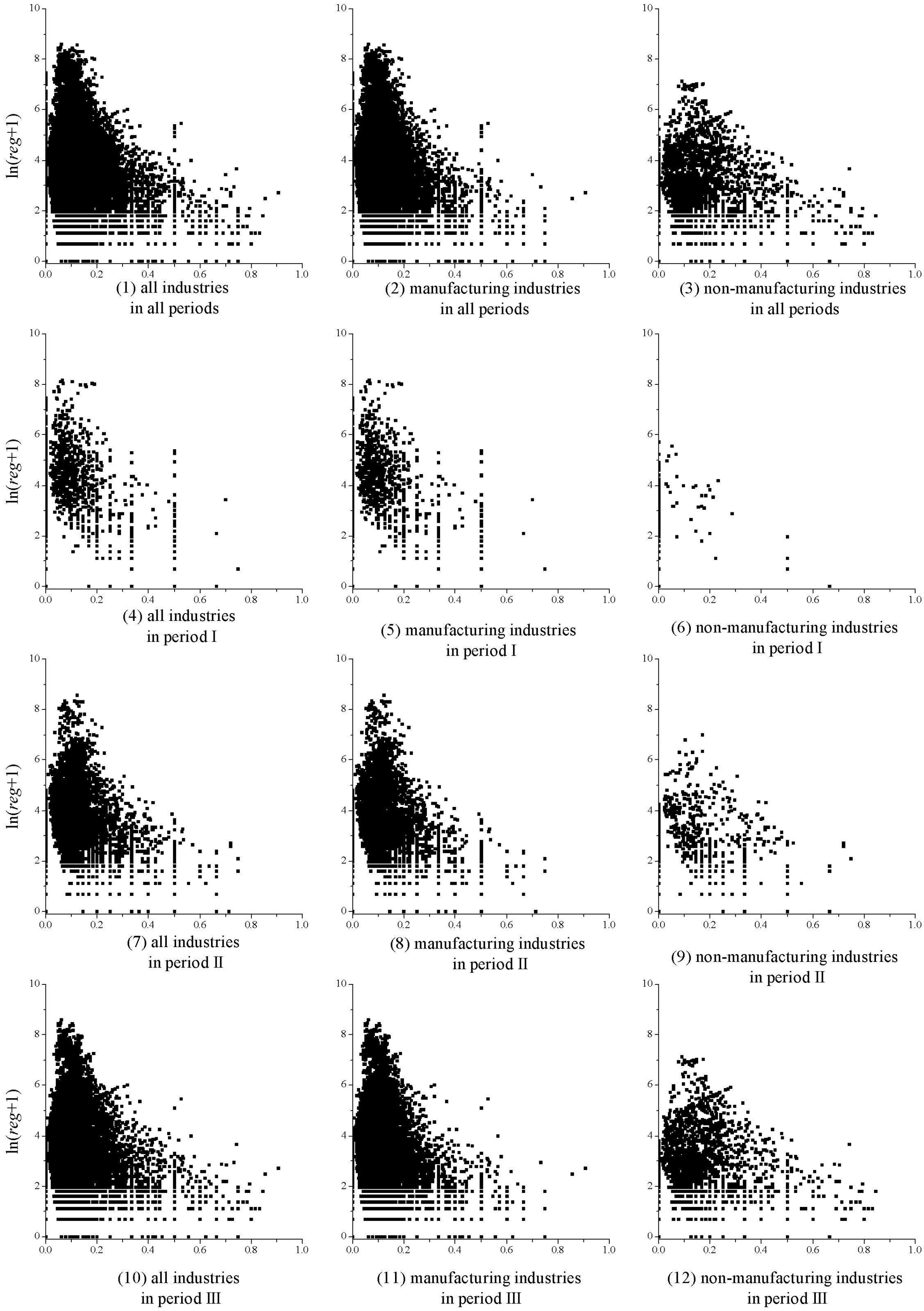


Figure A2. Scatter plot of depth toward ln(*reg*+1)

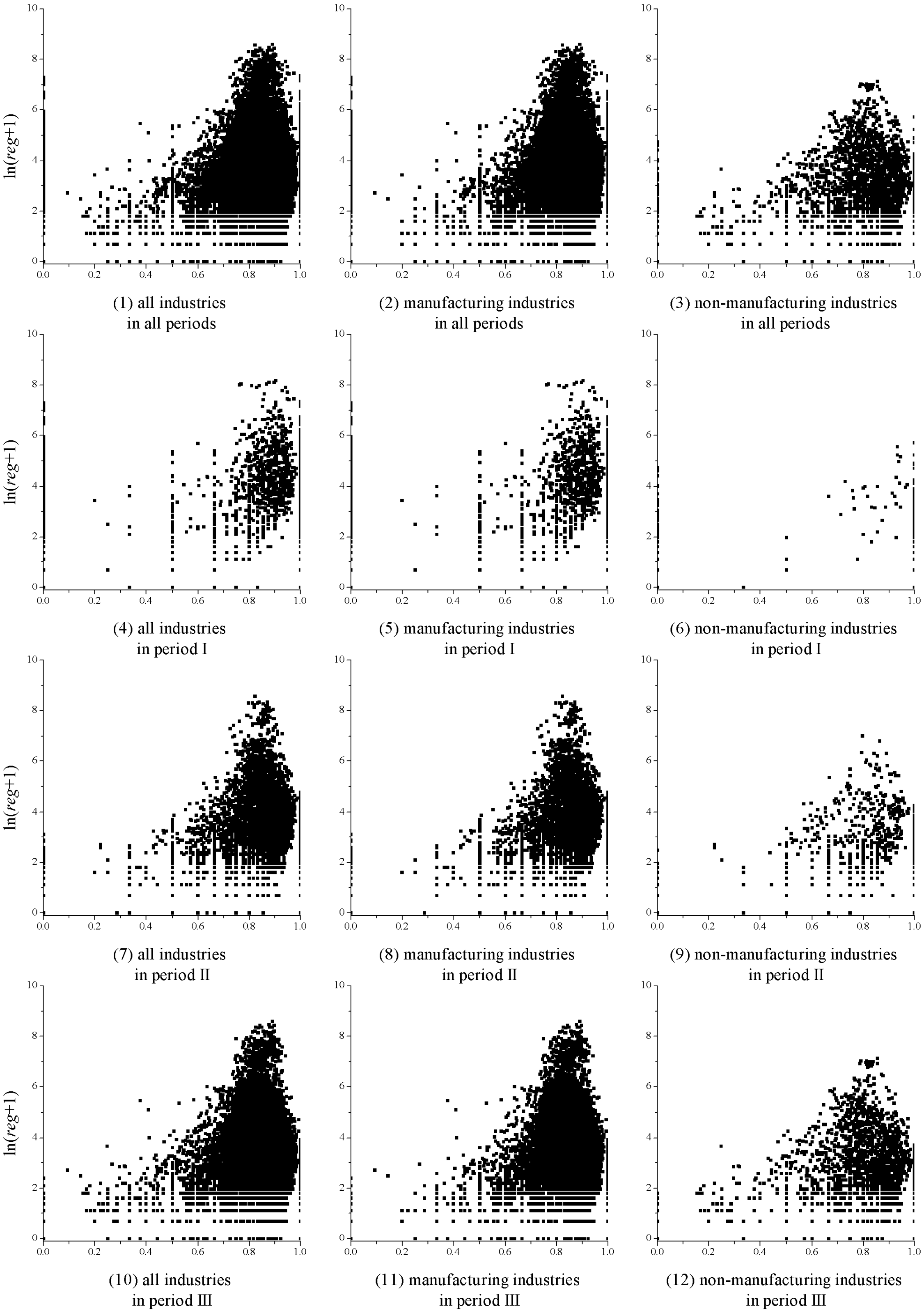


Figure A3. Scatter plot of scope toward ln(*reg*+1)