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R&D and Innovation: Evidence from Patent Data *

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We investigate innovation dynamics in Japanese listed firms by calculating an indicator for the accumulation of innovation based on patent citations, the "citation stock." The calculated citation stock has decreased since the mid-2000s, which implies that the pace of innovation accumulation at Japanese listed firms has slowed. Using the citation stock, we show that an increase in a firm's citation stock contributes to its productivity growth and that the citation stock provides information on whether research and development (R&D) leads to innovation that cannot be captured by focusing on the amount of R&D investment alone. In addition, we find that while higher R&D investment is associated with new innovation, the efficiency of R&D investment in Japan has decreased in recent years. Such a decrease in the efficiency of R&D investment has been reported not only for Japanese firms but also for a wide range of fields around the world, so that firms and research institutions are attempting to maintain the pace of innovation by increasing the number of researchers and research spending. For Japan, where it is difficult to increase the number of researchers due to the declining population, it is important to improve the quality of research through various efforts such as increasing the diversity of researchers.

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1 Introduction

What is the driving force of economic growth? This is an important question that has been discussed by researchers and policymakers for about a century. The simplest answer is that innovation drives economic growth.[1] In recent years, new technologies such as the internet of things (IoT) and artificial intelligence (AI) have been making rapid advances and the importance of innovation is increasingly recognized around the world. Against this backdrop, firms have been aggressively increasing investment in research and development (R&D).

As shown in Figure 1, R&D investment in Japan has generally followed an upward trend despite some temporary drops such as after the 2008 global financial crisis. Increases in R&D investment are expected to lead to increases in the productivity of Japanese firms in the future. Therefore, in order to forecast the future path of the Japanese economy, it is important to examine to what extent R&D investment results in innovation and improves firm productivity.

However, despite considerable efforts, researchers have not reached a consensus on how innovations occur and how they should be measured. Therefore, to examine innovation in Japan, we approach the topic from a variety of angles. In particular, we first examine developments in Japan by constructing proxy variables for innovation by Japanese firms. Further, we examine the extent to which innovation affects firms' productivity using panel data for Japanese firms. Finally, by analyzing to what extent recent R&D activities in Japan's manufacturing industries have contributed to innovation, we consider the impact of R&D activities by Japanese firms on future economic growth.

Specifically, our analysis consists of the following three steps. First, following the existing literature, we calculate two indicators—based on patent citations and R&D investment—as proxies to measure the knowledge and innovations held by firms. (Details of how the two indicators are calculated are provided in Section 2.) We find that while the indicator based on the R&D investment has remained more or less unchanged, the indicator based on patent citations (referred to as the "citation stock" hereafter) has been declining since the mid-2000s. Second, in the manufacturing sector, the citation stock has explanatory power with regard to firms' productivity, while the R&D stock does not have any additional explanatory power given the citation stock. This implies that the information on citations has more significant explanatory power with regard to firms' innovations than the R&D stock

[1] Since Schumpeter (1912) first highlighted the importance of innovation in economic growth, a growing number of researchers and policymakers have regarded innovation as the key driver of economic growth. Based on growth theory, we can decompose the growth rate in GDP per capita into changes in the capital-labor ratio and the technology level. In this study, we regard innovation as a factor that changes the technology level. See Hirata (2012) for details.

and that the citation stock includes information about the success or failure of R&D investments.

Furthermore, we estimate an econometric model of innovation in which the citation stock is the dependent variable and R&D investment is an explanatory variable. The estimation results indicate that the efficiency of R&D investment has been declining since the 2000s. Such a long-term trend of a decline in R&D investment efficiency has been reported not only for Japan but also for other countries including the United States (Gordon, 2016; Bloom et al., 2020). In other words, the decline in R&D investment efficiency is not unique to Japan.

Patent data are widely used in the United States and Europe for measuring social innovation, and analyses using relatively large-scale data can be traced back to the 1960s (see, e.g., Scherer, 1965, and Schmookler, 1966). Since then, a large body of research has sprung up linking patents to changes in the economic value of individual firms and to macroeconomic productivity as well (Pakes and Griliches, 1980; Griliches, 1981, 1984, 1998; Jaffe et al., 1993; Bloom and Van Reenen, 2002; Lanjouw and Schankerman, 2004; Hall et al., 2005; Bloom et al., 2013; Kogan et al., 2017; Kline et al., 2019). This proliferation of studies was greatly aided by Hall et al. (2001), who prepared and published patent data for the United States in a form that can be used for statistical analysis. In contrast, economic analyses using patent data for Japan have been limited, since Japan has been lagging behind in the availability of patent data that can be used for statistical analyses. Such data became available in 2005 with the release of the "IIP Patent Database" by the Institute of Intellectual Property, which opened the door for quantitative analyses on Japan (Goto and Motohashi, 2005). In this study, we will examine recent trends in innovation by Japanese firms using the same dataset, which we updated with more recent data.

What is more, a growing number of studies for the United States and Europe show that, among the various types of patent data, data on patent citations yield particularly robust results (Trajtenberg, 1990; Harhoff et al., 1999; Bloom and Van Reenen, 2002; Lanjouw and Schankerman, 2004; Hall et al., 2005). Similarly, for Japan it has been recently shown that information on patent citations provides a useful measure of the economic and scientific value of inventions (Yamada, 2009; Jibu and Osabe, 2014; Yasukawa, 2015, 2017). However, there are few studies that comprehensively examine the relationship between R&D investment and firm productivity using Japanese patent data from 2000 onward. Since many researchers regard the low growth rate of the economy during the period to be attributable to the low productivity growth of Japanese firms, it is of great significance to examine the link between innovative activity and firm productivity using patent data for the Japanese economy.

The remainder of this study is organized as follows. Section 2 explains how we calculate our proxy variables for innovation based on patent citation information and R&D investment, and presents the results using Japanese data for the period from the 1980s onward. Section 3 then examines the relationship between the calculated citation stock and firms' productivity. Next, Section 4 analyzes the relationship between innovation as measured by the citation stock and R&D investment, while Section 5 examines the reasons for the decline in the efficiency of R&D investment. Finally, Section 6 concludes and outlines topics for future research.

2 Patent Data and Innovations

This section explains how we use patent information as a proxy for innovation and provide an overview of innovation trends in Japan since 1980. We also calculate an indicator using R&D investment, which is often used as a proxy variable for the accumulation of new knowledge in companies and the economy.

2.1 Patent data and R&D investment as proxies for innovation

As mentioned, the importance of innovation as a source of growth for the macroeconomy has been recognized since the early 1910s. However, since innovation cannot always be directly observed, it is difficult to quantitatively capture and evaluate. Against this background, studies in the United States and Europe have frequently used patent data to measure innovation. The underlying idea is that if an invention has economic value, firms and individuals are likely to apply for a patent. Therefore, investigating a firm's patent holdings makes it possible to assess its accumulation of innovations. In addition, using patent data makes it possible to understand the importance of innovation by examining the relationship between patents and firms' value and/or productivity.

Another frequently used approach is to employ R&D investment. The approach is based on the idea that R&D investment leads to the accumulation of knowledge, which in turn increases firms' productivity through product and process innovation. Further, based on the idea that R&D investment contributes to production over a period of time, researchers have regarded R&D investment as a type of capital investment and have introduced the concept of "R&D stock" akin to capital stock, which yields capital services over time.[2] In fact, based on the idea that R&D in-

[2]Researchers focusing on the R&D stock include, for example, Corrado et al. (2009), who showed that intangible assets, including R&D stock, are a key factor in explaining labor productivity growth in the United States. Meanwhile, examining the link between firms' R&D stock on the one

vestment is useful for future production activities, it is included in Japan's SNA statistics as one of the components of total fixed capital. Based on these considerations, we construct (1) a proxy variable for the accumulation of new knowledge using patent information and (2) an indicator based on the amount of R&D investment.

2.2 Overview of the Japanese patent system

Before calculating the proxy variables for innovation, we provide an overview of the Japanese patent system. Japan's patent system is designed to protect the most advanced technical ideas that make use of the laws of nature. Article 1 of the Patent Act states: "The purpose of this Act is, through promoting the protection and utilization of inventions, to encourage inventions, and thereby contribute to the development of industry." The Patent Act is one element of the institutional framework for protecting intellectual property rights and stipulates that the rights of the inventor are protected for 20 years from the filing of the application. The Japan Patent Office publishes patent applications 18 months after they have been filed, and applicants need to make a request for examination within 3 years of the submission of the application. If the patent application is approved upon examination, the patent will be registered. Meanwhile, if a patent application is refused by the examiner of the patent office, the applicant can appeal or amend the application to address the reason for refusal. Figure 2 shows that while the number of applications peaked in the first half of the 2000s and has been on a gradual downward trend since then, the number of registrations has been on an increasing trend since 2000.[3]

2.3 Information on patent citations

This section explains how we measure the value of technology that is protected by patents using information on patent citations. In a patent application, the applicant may cite another patent, or the examiner may cite another patent as a reason for refusal.[4]

As mentioned, there have been a number of studies on the usefulness of such information on patent citations. Following these studies, we measure the value of a

hand and their market value and productivity on the other, Bloom et al. (2013) showed that there are positive spillover effects from the R&D investment of other firms that are similar in terms of their technology. As for Japan, Nagaoka (2006), Fukao et al. (2009), Motohashi (2009), and Tonogi and Tonogi (2016) examined the impact of R&D stock on productivity using Japanese data.

[3] Since, as described, there is a lag from the time an application is submitted until a patent is registered, many patents filed after 2015 were still not registered at the time we obtained our data (April 2019). This is the reason why the number of patent registrations in Figure 2 systematically declines from 2015 onward.

[4] The fact that a patent is frequently cited as a reason for refusal suggests that the invention in that patent is pathbreaking and likely to be useful for other uses.

patent using the number of other patents citing it (referred to as "forward citations"). That is, we regard the technology in patents that are frequently cited in other patents as versatile and having a high utility value.

Specifically, we count the number of times that a firm's patents are cited in other patents. That is, we calculate the cumulative number of citations ($CITE_{j,T}$) for T years after the filing of patent j as follows:

$$CITE_{j,T} = \sum_{\tau=t}^{t+T} cite_{j\tau},$$

where t is the year in which patent j was filed, and $cite_{j\tau}$ is the number of times patent j was cited in τ. If $T = \infty$, the number of lifetime citations of patent j can be calculated. However, a problem with this approach is that, by definition, it may result in a low cumulative number of citations for patents filed at the end of the observation period. To address this problem, previous studies such as Bloom et al. (2013) use the number of citations for a certain period after a patent application has been filed. Similarly, we set T=5.[5] To examine the actual pattern of citations in Japan, Figure 3 plots the frequency of citations against a timeline using patent data from January 2000 to December 2009. The figure shows that the number of citations peaks about two years after the application and that about 80% of citations occur within five years.

In order to link the calculated number of citations for each patent to firm-level data such as firms' productivity and corporate value, the patent data for each firm is then aggregated as follows (omitting subscript T for simplicity) to obtain the firm-level "citation flow" (CITEFLOW):

$$CITEFLOW_{it} = \sum_{j \in J_{it}} CITE_j,$$

where J_{it} is the set of patents filed at time t by firm i. CITEFLOW$_{it}$ calculated using the above formula is regarded to represent the value of the entire patents filed by firm i in year t.

[5]To check the robustness of our results, we also used three years (T=3), but the main results remained qualitatively unchanged.

2.4 Calculation of patent citation stock and R&D stock

Next, based on the idea that it is the stock of innovations that underpins a firm's corporate value and productivity, we calculate the citation stock for firm i as follows:

$$CITESTOCK_{it} = CITESTOCK_{it-1}(1 - \delta_c) + CITEFLOW_{it},$$

where δ_c represents the depreciation rate of assets. Following previous research, we set $\delta_c = 0.3$.[6]

Another variable widely used in previous research to represent innovative activity is the R&D stock, which is calculated as follows based on R&D investment flows:

$$R\&DSTOCK_{it} = R\&DSTOCK_{it-1}(1 - \delta_R) + R\&D_{it},$$

where δ_R is the depreciation rate of R&D stock, which is set to 0.15 following previous research,[7] and $R\&D_{it}$ is real R&D investment obtained by deflating nominal R&D investment using the GDP deflator.

We use the patent citation stock and the R&D stock as two alternative variables to gauge knowledge accumulation within the firm through R&D activities. However, the two differ in that patent citations can be regarded as measuring the output of R&D activities, while the R&D stock can be regarded as measuring the input of resources into R&D activities, as Lanjouw and Schankerman (2004) pointed out. It should further be noted that the R&D stock can be calculated only for firms that disclose their financial information. In contrast, the citation stock can be calculated for all patent-holding firms, since patent information is in the public domain. That said, since information on patents is released only one and a half years after an application has been filed, the data are available only with a lag. Furthermore, firms do not apply for a patent for all inventions.

2.5 Developments in firms' citation stock and R&D stock

Next, we calculate the citation stock and R&D stock based on the approaches just described.

To calculate the patent citation stock, we use the "IIP Patent Database (2017 version)" provided by the Institute of Intellectual Property. However, since this database does not contain data for the period after 2017, we combine it with another database (PatentSquare), which includes all patent data available as of October

[6] Yamada (2009) estimates the depreciation rate δ_c based on Japanese patent renewal data and shows that it is approximately 0.3.

[7] As a robustness check, we also set $\delta_R = 0.3$. However, doing so did not affect the estimation results and conclusions of our analysis.

2019. To be able to compare developments in firms' citation stock with firms' R&D stock, we focus on firms listed on the first and second sections of the Tokyo Stock Exchange, for which financial information on their R&D expenditure can be obtained. Firms' financial information is taken from the "Industrial Financial Data" compiled by the Development Bank of Japan.

Figure 4 shows that the citation stock is higher in the manufacturing sector than in the non-manufacturing sector, partly because patentable inventions are limited to those that "use the laws of nature." In addition, the citation stock in the non-manufacturing sector has been on a downward trend since the early 1990s, while that for the manufacturing sector continued to follow an upward trajectory until the early 2000s. Since then, however, the citation stock in the manufacturing sector has also followed a downward trend.

Next, Figure 5 shows the citation stock by industry, focusing on the six manufacturing industries most active in R&D that account for most of the R&D investment. The average citation stock is highest in the transportation equipment and the electric appliances industries, followed by the chemical and precision instruments industries. Taking a closer look at developments over time, the citation stock in the transportation equipment industry peaked in the early 2000s and has been on a downward trend since. On the other hand, that for the precision instrument industry continued to rise until the mid-2000s and then began to decline. Thus, although the turning points slightly differ across industries, the citation stock overall has been declining since the latter half of the 2000s.

On the other hand, as shown in Figure 6, the R&D stock overall, calculated based on R&D investment, remained more or less unchanged over the entire observation period. However, while the R&D stock in the manufacturing sector has been on a slight upward trend since the second half of the 2000s, that in the non-manufacturing sector has been on a more or less consistent downward trend since the early 2000s. Moreover, the R&D stock in the non-manufacturing sector is considerably lower than in the manufacturing sector.

Comparing the citation stock and the R&D stock shows that both have been on a downward trend since the 2000s in the non-manufacturing sector. On the other hand, in the manufacturing sector, the citation stock has been declining since the second half of the 2000s while the R&D stock has continued to rise. Although not shown here, data on the R&D stock by industry show that the continued increase in the manufacturing sector R&D stock overall largely owes to active R&D investment in the transportation equipment industry. In the next three sections, we examine the usefulness of both stocks as proxy variables for innovation by analyzing the relationship between the citation stock and R&D stock on the one hand and firm productivity on the other.

3 Innovation and Productivity

In this section, we investigate whether our two proxy variables help to explain firms' productivity level.

3.1 Production function in the baseline model

Previous studies, based on the idea that innovations and new knowledge contribute to firms' productivity growth, have incorporated the citation stock and the R&D stock as factors of production (e.g., Hall et al., 2005; Bloom et al., 2013). Following these studies, we assume the following Cobb-Douglas production function:

$$Y_{it} = A_{it} K_{it}^{\alpha} N_{it}^{\gamma} L_{it}^{1-\alpha-\gamma},$$

where Y_{it} is the output of firm i in year t. K, N, and L represent tangible fixed assets, the innovation stock (citation stock or R&D stock), and labor input, respectively. A_{it} is the residual. In this basic production function, what is not explained by N, K, or L is called the Solow residual and is often regarded as representing total factor productivity (TFP). Taking the logarithm of both sides of the above equation yields the following model, which we use for the estimation:

$$y_{it} = \alpha k_{it} + \gamma n_{it} + (1 - \alpha - \gamma) l_{it} + a_{it},$$

where lowercase letters represent the log of the corresponding variables in the equation above. Furthermore, given that the residuals may include unobserved effects unique to each firm, we include firm fixed effects. In addition, we control for changes in the macroeconomic environment as follows:

$$y_{it} = \alpha k_{it} + \gamma n_{it} + (1 - \alpha - \gamma) l_{it} + YearFE_t + \omega_i + \epsilon_{it}, \tag{1}$$

where $YearFE_t$ is the fixed effect for year t. Since model (1) takes firm fixed effects into account, we do not need to consider time-invariant fixed effects for each industry.

However, to take into account that industry-specific demand shocks may affect production activities, we also estimate the following model with a time dummy for each industry:

$$y_{it} = \alpha k_{it} + \gamma n_{it} + (1 - \alpha - \gamma) l_{it} + IndustryYearFE_{ht} + \omega_i + \epsilon_{it}, \tag{2}$$

where $IndustryYearFE_{ht}$ is the fixed effect at time t for industry h to which firm i belongs. In this model, common shocks to output in each industry in each year are controlled for by the fixed effect. The results of estimating models (1) and (2) are presented in Section 3.3.[8]

3.2 Data

The dependent variable in our estimation is firms' real gross value added. Specifically, we subtract firms' intermediate input costs from their sales and convert nominal gross value added into real gross value added using industry-level GDP deflators. For real tangible fixed capital, nominal tangible fixed assets are converted into real values using the industry-level capital investment deflators from the Japan Industrial Productivity (JIP) Database. For labor input, we divide firms' total salary payments calculated from their financial statements by the wage index for total cash salaries from the "Monthly Labour Survey" compiled by the Ministry of Health, Labour and Welfare.

We set the start of the estimation period to fiscal 2000, from when data on R&D investment are available. The end is set to fiscal 2012, the last year for which we can calculate intermediate input costs and the patent citation stock. In addition, in order to ensure the number of observations is sufficiently large, we use non-consolidated financial data for individual firms. In our analysis, we focus on the six manufacturing industries (chemicals, pharmaceuticals, machinery, transportation equipment, electric appliances, and precision instruments) that have been the most active in conducting R&D in recent years.

3.3 Estimation results

This section presents our estimation results. Table 1 shows the estimation result for the production function. We find that the coefficients on tangible fixed capital input and labor input are generally positive and statistically significant. Note that, following Bloom et al. (2013), we do not assume that the production function is homogeneous of degree one, which would imply that the sum of the coefficients is one.[9] Column (1) in the table shows the estimation results for model (1) with the R&D stock as an explanatory variable. The estimated coefficient on the R&D stock is positive and significant. Similarly, when the citation stock is used instead of the

[8] To address potential endogeneity in productivity shocks, we also estimate the model using Olley and Pakes's (1996) approach.

[9] The estimation results show that the sum of the coefficients, which indicates the elasticity of scale, is about 0.7, which is smaller than 1. The fact that the sum of the estimated coefficients is relatively small may be due to endogeneity in productivity shocks. When we conducted the estimation using Olley and Pakes's approach (1996), the sum of the coefficients is around 1, and qualitatively the same conclusions as those derived from the fixed effects model are obtained. However, since Olley and Pakes's approach relies on instrumental variables, the number of observations decreases and the problem of weak instruments arises. This is why in our analysis we focus on the results of the fixed effects model following Bloom et al. (2013).

R&D stock, as shown in column (2), the coefficient on the citation stock is positive and significant.

Next, column (3) shows the results for the model in which both the citation stock and the R&D stock are added contemporaneously as explanatory variables to model (1). We find that both coefficients are positive and significant. Finally, column (4) shows the results for the model shown in equation (2), in which industry- and year-specific demand shocks are controlled for. The coefficient on the R&D stock is no longer significant, while that on the citation stock is still positive and significant. This suggests that the citation stock has greater explanatory power than the R&D stock in accounting for productivity differences across firms, which is in line with Hall et al.'s (2005) results using US data. This is also consistent with the results obtained by Yamada (2009) using Japanese data.

The different estimation results for R&D stock and the citation stock can be explained by considering what each of the stocks represents with regard to firms' R&D activities. An increase in R&D stock does not necessarily mean that a firm generates more innovative products. Rather, the degree to which R&D activities are successful can change over time depending on the external environment. Therefore, the relationship between the R&D stock and the number of innovative products is likely to be unstable. In contrast, firms generally apply for a patent when they think that an innovation has a high economic value, and only those patents that are useful for generating other innovations are cited in other patents. In other words, the number of citations of firms' patents indicates whether its R&D activities are successful or not.

To confirm this point from other data, we compare the average growth rate of the citation stock and that of TFP taken from the JIP Database provided by the Research Institute of Economy, Trade and Industry (RIETI). Figure 7 shows that there is a positive correlation between the two. Furthermore, using industry panel data, we estimate a fixed effects model using the growth rate of TFP as the dependent variable and the growth rate of the citation stock as the explanatory variable. The result is shown in Table 2 and indicates that the coefficient is positive and significant. On the other hand, the coefficient on the R&D stock is not statistically significant, since R&D investment was already taken into account as a factor of production in the calculation of TFP by researchers at RIETI. The estimation results provide evidence that the citation stock still contains additional information on productivity even when R&D investment is taken into consideration. That is, the results imply that the citation stock contains information on the success or failure of R&D activities that is not captured by focusing on the amount of R&D investment.

3.4 Robustness check: An alternative measure of the citation stock

As highlighted in previous studies, changes in the citation stock may reflect changes in the patent system. To minimize the impact of changes in the patent system on the citation stock, we use only citations made by patent examiners, since there do not appear to have been any changes during the estimation period in the rules concerning the citation of patents by examiners. However, it is possible that the citation stock may have been affected by other changes in the patent system.

In order to take this into account, we estimate the production function using an alternative measure of the citation stock.

Specifically, we weight citations by the relative importance of a patent in each technology class in the International Patent Classification (IPC). [10] That is, the adjusted citation flow ($CITEFLOWAD_{it}$) of firm i is calculated as follows:

$$CITEFLOWAD_{it} = \sum_{j \in J_{it}} CITE_j / MEAN_{k_j t},$$

where k_j represents the IPC classification of patent j, and $MEAN_{k_j t}$ indicates the average number of forward citations of patents whose IPC classification is k_j. The number of citations calculated using the above formula is considered to represent the relative importance of patent j in each IPC classification in each year. Therefore, even if the average number of citations by examiners varies over the years due to institutional factors, $CITEFLOWAD_{it}$ will take a value of around one for patents of average importance regardless of the year of filing. Using the citation flow calculated as above, we aggregate the adjusted citation stock (CITESTOCKAD) for each firm and estimate the production function.

Table 3 shows that the coefficient on the adjusted citation stock (CITESTOCKAD) is positive and statistically significant, while the coefficient on the R&D stock is not significant. This result implies that changes in the pattern of citations by examiners do not affect our findings.

4 R&D and Innovation

This section examines to what extent R&D activities can explain the generation of innovation, and whether the link between R&D activities and innovation has

[10] The IPC, established by the 1971 Strasbourg Agreement, is a technical classification of international patents. It consists of eight major sections from A (human necessities) to H (electricity), which are further subdivided into classes, subclasses, and groups. We use the 128 classes represented by one letter and two digits.

changed since the 2000s. As a proxy variable for innovation, we use the patent citation flow (CITEFLOW), where the number of patents a firm holds is weighted by the number of their citations.

4.1 Innovation function

Following previous studies (Griliches et al., 1986; Branstetter and Nakamura, 2003; Lanjouw and Schankerman, 2004, etc.), we assume that firms invest in R&D in order to generate innovation. Therefore, we formulate the following innovation function:

$$NEWK_{it} = RC_{i,t}^{\theta} Control_{it} B_t,$$

where $NEWK_{it}$ represents innovation newly created by firm i that can be used for production activities. RC_{it} represents the resources used as R&D input at firm i at time t, $Control_{it}$ represents other control variables, and B_t is the year fixed effect. Taking the log of both sides of the above equation yields the following:

$$newk_{it} = \theta log(RC_{it}) + \beta_0 sales_{it} + \rho_{nh} IndDum_h + YearFE_t + \epsilon_{it},$$

where $newk_{it}$ is the log of new innovative technologies, $Newk_{it}$. $IndDum_h$ is a dummy variable for industry h to which firm i belongs, and $YearFE_t$ is the fixed effect for year t. Previous studies have pointed out that firm size affects the efficiency of R&D and therefore added sales to the estimation equation. However, since R&D investment in the current period does not always lead to innovation in the same period, we use the following model taking into account the possibility that R&D investment generates innovation with lag:

$$newk_{it} = \sum_{\tau=0}^{n} \theta_\tau r_{i,t-\tau} + \beta_0 sales_{it} + \rho_{nh} IndDum_h + YearFE_t + \epsilon_{it}, \tag{3}$$

where $r_{i,t-\tau}$ is the log of real R&D investment, and $r_{i,t-\tau} = log(RC_{i,t-\tau})$. Next, it is assumed that the patent flow is proportional to the innovations that are produced. Specifically, the following relationship is assumed:

$$CITEFLOW_{it} = \mu_{it}^{c} NEWK_{it}. \tag{4}$$

The above equation means that we assume that some of the new innovative technologies (μ_{it}^{c}) have been filed as patents and appear in the citation information. Taking the log of equation (4) and assuming that μ_{it}^{c} differs for each industry, we can rewrite the above equation as follows:

$$log(CITEFLOW_{it}) = newk_{it} + \rho_{ch} IndDum_h + \eta_{it}, \tag{5}$$

where η_{it} is the residual.

Furthermore, by combining equations (3) and (5), $CITEFLOW_{it}$ can be expressed as follows:

$$\begin{aligned} log(CITEFLOW_{it}) = & \sum_{\tau=0}^{n} \theta_\tau r_{i,t-\tau} + \beta_0 sales_{it} + (\rho_{nh} + \rho_{ch}) IndDum_h \\ & + YearFE_t + \eta_{it} + \epsilon_{it}. \end{aligned} \tag{6}$$

In the next subsection, we analyze the relationship between R&D investment and innovation by estimating equation (6). In particular, we examine whether R&D efficiency has declined since the latter half of the 2000s. Specifically, we do so by looking at developments in the year fixed effect ($YearFE_t$) in equation (6).[11]

4.2 Estimation results

Table 4 shows the estimation results of the baseline model with R&D lag orders of $n = 0, 2, 5$. The estimated coefficient on R&D investment is about 0.3 when n = 0. It should be noted that, as pointed out by Griliches et al. (1986), the relationship between the citation flow and R&D spending is not affected by the choice of lag order when R&D investment follows a highly autocorrelated process. We can calculate the sum of lag coefficients to analyze the impact of R&D investment on innovation. In the case of n = 2,5, the sum of the coefficients of the R&D term is about 0.3 and significantly different from zero regardless of the lag order. This means that a 1% increase in R&D investment will increase the citation flow by 0.3%.

The estimated industry effects, which are estimated using chemicals as the reference industry, are negative for pharmaceuticals and transportation equipment, while they are positive for electric appliances, as shown in Table 5.[12] A possible reason for the negative industry effects in the pharmaceutical and transportation equipment industries is that the number of patents obtained relative to the amount of R&D investment is quite low, as shown in Figure 8.

Finally, the estimated year fixed effect follows a downward trend. This implies

[11] In order to examine changes in R&D efficiency, we could also use a different specification in which the elasticity of R&D investment, θ, varies over time. To check the robustness of our results, we also estimated the alternative model with time-varying θ. The results confirm that R&D efficiency has declined since the second half of the 2000s. However, following previous studies such as Branstetter and Nakamura (2003), we report only the results focusing on year fixed effects.

[12] The estimation results in Table 5 are for n = 0, which yields the largest number of observations.

the return on R&D investment in terms of patents obtained has declined since the 2000s, as shown in Figure 9. This result suggests that the efficiency of R&D investment in Japanese firms has declined in recent years. There are various possible reasons for this decrease in efficiency. These are considered in Section 5 and their plausibility is considered. Before that, however, we check the robustness of the above findings using an alternative specification of the innovation function that includes firm fixed effects and the alternative variable of the citation stock.

4.3 Robustness check

4.3.1 Innovation function

The innovation function estimated in the previous section did not take firm fixed effects into account. This section shows that the efficiency of R&D is still decreasing even when firm fixed effects are considered. That is, we estimate the following model, in which the fixed effect α_i for firm i is added to equation (6):

$$log(CITEFLOW_{it}) = \sum_{\tau=0}^{n} \theta_\tau r_{i,t-\tau} + \beta_0 sales_i t + YearFE_t + \alpha_i + e_{it}. \qquad (7)$$

Figure 10 indicates that although the rate of decline in the first half of the 2000s is smaller than in the baseline estimation, the year fixed effects is still decreasing, implying that the efficiency of R&D has been falling.

4.3.2 Adjusted citation flow

As pointed out in Section 3, the citation information may be affected by changes in the patent system. Therefore, we estimate the innovation function using the adjusted citation flow (CITEFLOWAD) as an independent variable. Figure 11 shows that the estimated year fixed effects decrease over time, although the pace of decrease is slower than in the baseline model. In other words, the amount of R&D investment required to achieve the same amount of citation flows has increased since the 2000s. Although not shown here, similar results were obtained estimating this model including firm fixed effects.

4.3.3 Changes in the tendency to apply for patents

A possible reason for the change in the link between the citation flow and R&D investment is that firms may have become less likely to apply for a patent due to changes in the patent system or in corporate patent strategies. To check whether this is the case, we calculate the ratio of the number of patent applications to the number of inventions. The result is shown in Figure 12 and indicates that this ratio has been on an upward trend since 2008. Furthermore, as shown in Figure 8, although the ratio of the number of patents obtained to the amount of the R&D investment shows different dynamics across industries, it has not declined since 2000.

To show that the tendency of firms to apply for patents has not changed, we estimate a patent registration model. Specifically, we replace the dependent variable in the citation flow model given by equation (6), $CITEFLOW_{it}$, with the number of patents granted. Figure 13 shows that the year fixed effect has hardly changed over time, indicating that the tendency of firms to apply for patents has not changed significantly in recent years.

5 Reasons for the Decline in R&D Efficiency

The results of the analysis so far suggest that the efficiency of R&D in Japan's manufacturing sector has been declining. This section presents possible explanations and discusses their plausibility.

The first possible explanation is that R&D efficiency has declined due to the intensification of R&D competition in recent years. For instance, the R&D expenditure of Chinese and Korean firms has been increasing rapidly since the 2000s. With these firms filing patents in many fields, it may have become more difficult for Japanese firms to obtain high-value patents. Figure 14, shows that China's R&D expenses overtook Japan's in the late 2000s. Moreover, since 2008, R&D expenditure in countries such as China, South Korea, and Taiwan has been growing at a faster pace than in Japan, pointing to intensifying R&D competition for Japanese firms.

The second possible explanation is that the quality and diversity of researchers in Japanese firms may be insufficient. Figure 15 shows that Japanese firms' personnel expenses per researcher followed a downward trend until the first half of the 2010s, although they have risen slightly in recent years. This suggests that Japanese firms have not been trying very hard to attract leading researchers, which may have led to top researchers joining firms overseas (Yamauchi et al., 2014). In recent years, it has been pointed out that the importance of "superstar" researchers has increased (Azoulay et al., 2010; Benzell and Brynjolfsson, 2019). The decline in personnel expenses per researcher at Japanese firms suggests that Japanese firms may have failed to attract such "superstar" researchers, which may have led to a slowdown in innovation. Further, as shown in Figure 16, the number and share of female researchers at Japanese firms remain low, providing one indicator that researcher diversity probably remains limited.[13] Given that, as highlighted by Jones (2009), the time and knowledge required to make innovative discoveries are rising, increasing researcher diversity seems essential to boost innovation.

The third possible explanation is that Japanese companies did not aggressively advance into new technological areas. Previous studies on innovation, particularly in the field of business studies, classify innovations into explorative and exploitative ones (see, e.g., March, 1991). Furthermore, a number of studies (e.g., Levinthal and March, 1993; Zhou and Wu, 2010) have pointed out that as a firm's knowledge in an existing technological field increases through experience, its incentives for developing new technologies decline.[14] Given these findings and the increasing average age of Japanese listed firms, it is possible that the aging of firms has reduced their appetite to enter new fields and pursue exploratory R&D.[15]

To further investigate this point, following previous research by Ahuja and Lampert (2001) and Kotha et al. (2011), we measure the extent to which firms have obtained patents in a new technical field. Specifically, we calculate the patent stock in a new area ($NewPatStock_{it}$), that is, the number of patents obtained in a technical field in which a firm previously had not obtained any patents. To obtain the patent stock in a new area, we first calculate the patent flow in the new area ($NewPatFlow_{it}$). Based on the flow, we then calculate the stock using the permanent inventory method:[16]

$$NewPatFlow_{it} = \sum_{k=1}^{N} P_{ikt}\delta_{ikt}, \tag{8}$$

where P_{ikt} represents the number of patents obtained by firm i in IPC classification

[13] That diversity is important for innovation and that there is a positive relationship between the diversity and growth of a firm, not just in the field of R&D, has been highlighted since the 1950s (e.g., Penrose, 1959). In fact, previous studies such as Ostergaard et al. (2011) have shown that there is a positive correlation between employee diversity in terms of gender and other characteristics and innovation.

[14] In the field of economics, Akcigit and Kerr (2018) used an endogenous growth model to theoretically show that incumbents tend to prefer exploitative R&D, while new entrants prefer exploratory R&D.

[15] Previous studies have not reached a consensus as to whether older firms become less likely to innovate. For example, Cohen and Levinthal (1990) point out that knowledge accumulation (absorptive capacity) is useful for capturing new external information and innovating, and knowledge accumulation takes time. They therefore argue that the older a firm gets the more likely it is to innovate. On the other hand, comparing existing companies and new entrants, Reinganum (1983) showed that existing monopolists have a weaker incentive to innovate than new entrants because they fear that new products would cannibalize their existing products. In the field of business studies, there is also a large body of research on innovation. An example is the study by Christensen (1997), which presents the idea of the innovator's dilemma. See Benner and Tushman (2003) for more details.

[16] When calculating the patent stock in new fields, we set the depreciation rate to 0.3. However, setting it to 0.15 does not affect the conclusions of our analysis.

k for the period from t to $t+2$. δ_{ikt} is a dummy for firms' entry into a new field and takes a value of one when firm i first obtains a patent in classification k at time t. Figure 17 shows the extent to which firms in a particular industry have obtained patents in a new field. Although most industries showed an upward trend in the early 2000s, other than for the electric appliances industry, the trend has been downward in recent years.

As mentioned above, the decline in the obtaining of patents in new technological fields may be due to the aging of firms. Therefore, in order to investigate the link between firms' age and patent flow in new fields, we estimate the following model, in which the patent flow in new fields is used as the dependent variable and firms' age is the key explanatory variable:

$$log(NewPatFlow_{it}) = \beta_1 log(Age_{it}) + \beta_2 X_{it} + \gamma_h IndDum_h + YearFE_t + \epsilon_{it}, \quad (9)$$

where Age_{it} is the number of years since firm i was established and X_{it} is a set of control variable. As control variables, we use the return on assets (ROA), total assets, the growth rate of sales, and the citation stock (all with a one-period lag).

The results are presented in Table 6 and indicate that younger firms tend to be more active in terms of expanding into new fields.[17] Furthermore, in order to examine how changes in the patent flow in new areas affects innovation, we estimate the innovation function adding the patent stock in new areas to the explanatory variables. The results are presented in Table 7, which shows that the estimated coefficient on the patent stock is positive and significant. This suggests that the reluctance to enter new technological fields may have reduced innovation.

That said, both theoretical and empirical research suggest that entering new technological fields does not always lead to an increase in innovation.[18] Nevertheless, the estimation results in Table 7 imply that firms that entered new fields have tended to generate a larger number of innovations. The findings here therefore suggest that the recent decline in entry into new fields by Japanese firms makes innovation less

[17]The estimation is based on ordinary least squares (OLS) regression using data for six manufacturing industries spanning a period of five years from 2008 to 2012. In addition, in order to check the robustness of the results, we estimated a Poisson regression model in which the patent flow in new fields was used as the dependent variable. The results of the Poisson regression also showed a significant negative relationship between firms' age and the patent flow in new fields.

[18]On the one hand, Garcia-Vega (2006), for example, reports that companies with diverse technologies are more likely to innovate and have a higher probability of survival. Similarly, Quintana and Benavides (2008) show that a diversified technological base enhances firms' ability to innovative, especially in the area of exploratory innovation. On the other hand, Kotha et al. (2011) find that the relationship between entry into new fields and innovation follows an inverted U-shape. Although entry into some new fields tends to lead to new innovations, entering into too many new fields leads to a decentralization of resources including researchers and an increase in adjustment costs, which reduces the efficiency of innovation. The data used in this study do not provide evidence of such an inverted U-shaped relationship.

likely to occur.

The fourth possible explanation is that the decline in the efficiency of R&D activities of Japanese firms simply reflects that generating innovations may be getting more difficult and as such is part of a phenomenon observed worldwide. As pointed out in a large number of studies (e.g., Jones, 2009; DiMasi et al., 2016; Gordon, 2016; Bloom et al., 2020), not only in Japan does innovating appear to be getting more difficult in a variety of fields such as medicine, agriculture, semiconductors, etc. If there is indeed such a secular trend, Japanese firms, of course, cannot escape from this in the long run. Under these circumstances, firms and research institutions in countries around the world are trying to maintain the pace of innovation by increasing the number of researchers and increasing joint research.

The above four possible explanations are closely related and it is difficult to examine the exact causal relationships among them. Moreover, it is beyond the scope of this study to quantitatively examine the contribution of the different factors to the decline in the R&D efficiency of Japanese firms since the 2000s. Examining the decline in R&D efficiency in more detail, including the above possible explanations, would be useful in considering measures to strengthen the long-term growth potential of Japanese firms.

6 Conclusion

In this study, we calculated the citation stock using patent data as a proxy variable for the innovation firms have accumulated and showed that the citation stock plays a significant role in explaining firms' productivity. Moreover, using the citation stock as a proxy variable for innovation, we also showed that the efficiency of firms' R&D activities have declined since the 2000s.

Finally, it should be noted that the quantitative analysis in this study focused only on the manufacturing sector, which conventionally has accounted for the bulk of R&D investment. In recent years, however, a major field of innovation has been technologies such as AI and IoT, the application of which is not necessarily limited to the manufacturing sector. Given the versality of technologies such as AI, it is possible that new innovations may be brought about by successfully incorporating such technologies in other technical areas and product fields. Analysis of the impact of technological progress in areas such as AI and IoT on innovation is an issue we leave for future research.

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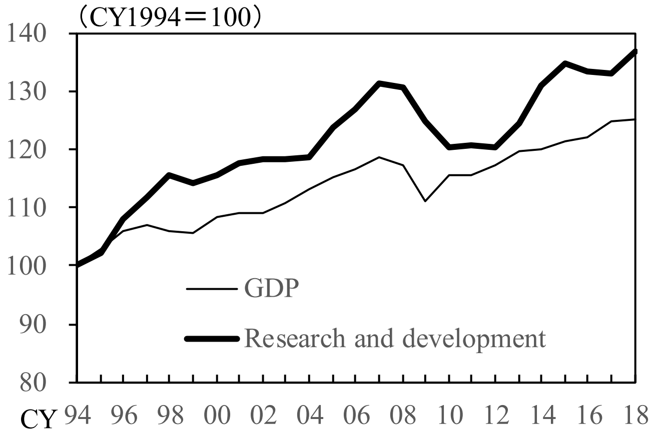
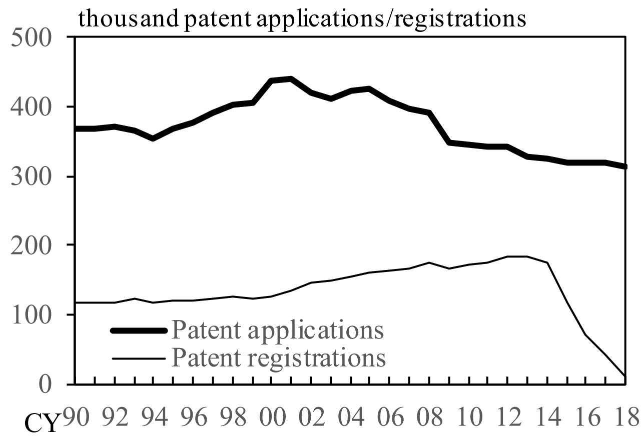
Figure 1: R&D Investment



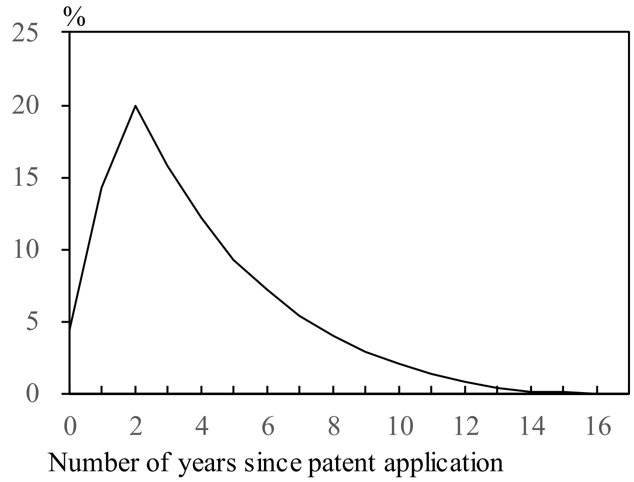
Source: Cabinet Office.
Note: Real values standardized to CY1994=100.

Figure 2: Number of Patent Applications and Registrations



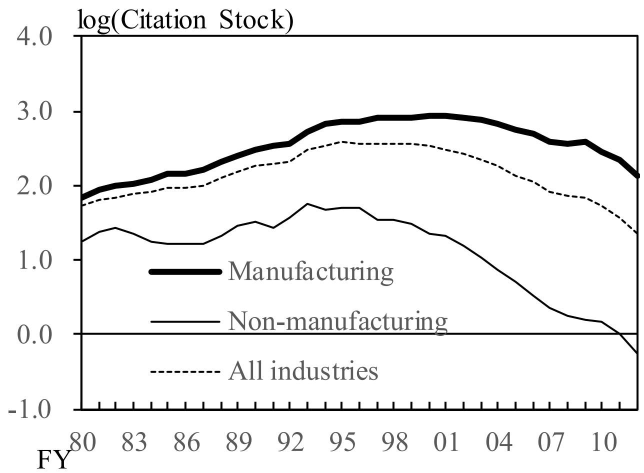
Source: Patent Office.
Notes: As of April 2019. The horizontal axis represents the year in which a patent was applied for.

Figure 3: Forward Citations Over Time



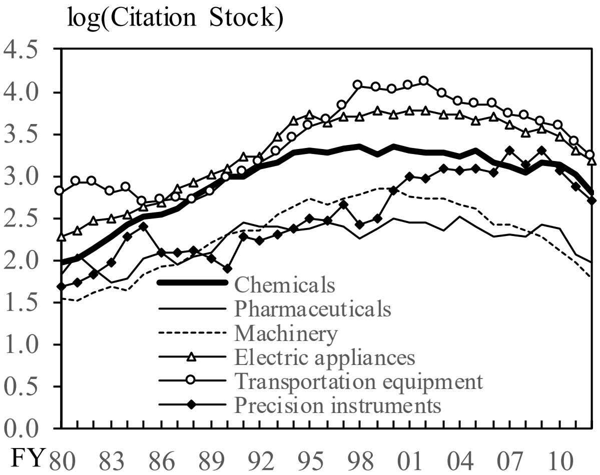
Sources: Institute of Intellectual Property, "IIP Patent DB;" PatentSquare.
Notes: The horizontal axis represents the number of years since the application for the cited patent, while the vertical axis represents the percentage of the number of citations over the 16 years

Figure 4: Citation Stock



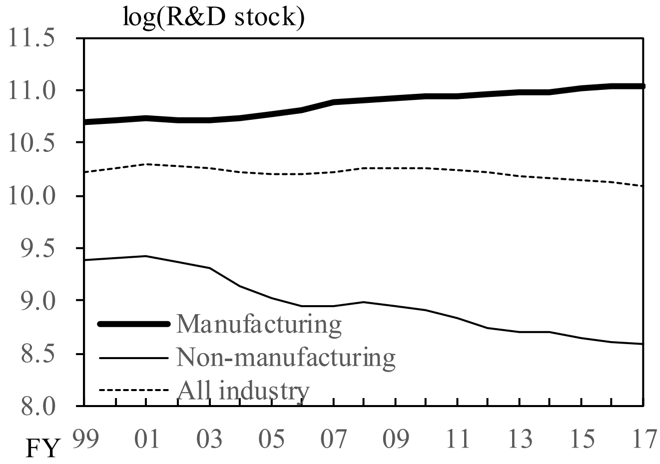
Sources: Institute of Intellectual Property, "IIP Patent DB;" PatentSquare; Patent Office.
Note: The figure shows the averages for firms listed on the first and second sections of the Tokyo Stock Exchange.

Figure 5: Citation Stock by Industry



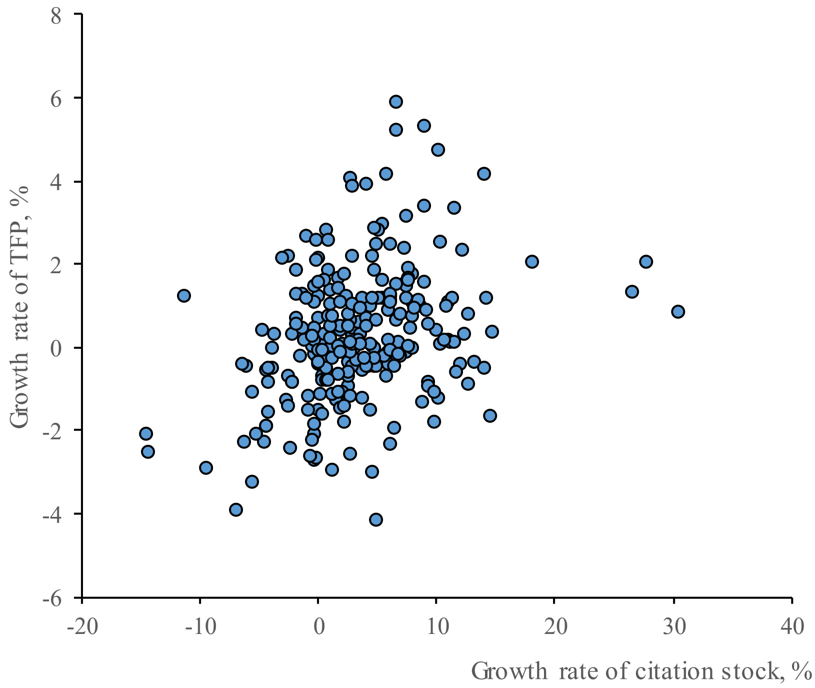
Sources: Institute of Intellectual Property, "IIP Patent DB;" PatentSquare; Patent Office.
Note: The figure shows the averages for firms listed on the first and second sections of the Tokyo Stock Exchange.

Figure 6: R&D Stock



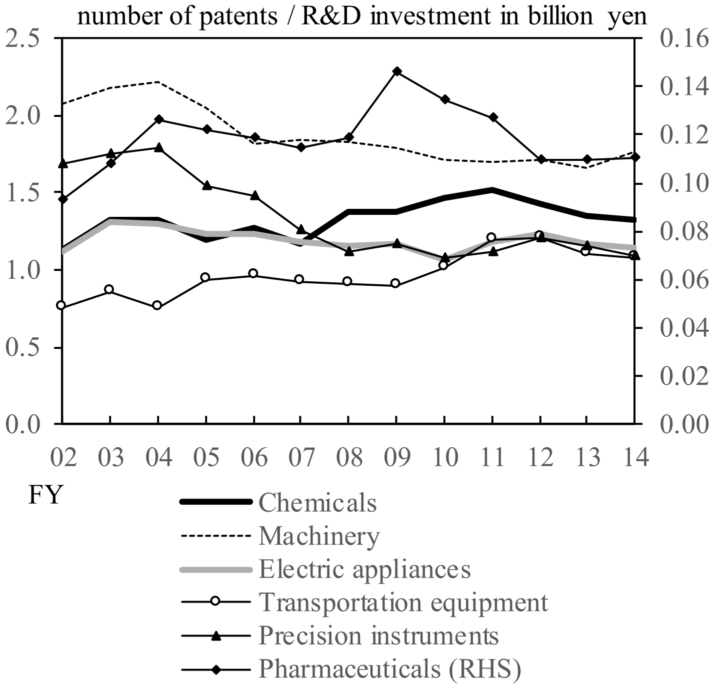
Source: Development Bank of Japan.
Note: The figure shows the averages for firms listed on the first and second sections of the Tokyo Stock Exchange.

Figure 7: Citation Stock and TFP from the JIP Database



Sources: JIP Database; Institute of Intellectual Property, "IIP Patent DB;" PatentSquare; Patent Office.
Notes: The vertical axis shows the TFP growth rate from year *t* to *t*+2 by industry for manufacturing industries. The horizontal axis shows the growth rate of the citation stock from year *t*-3 to *t*-1. The figure covers the period from 1997 to 2012.

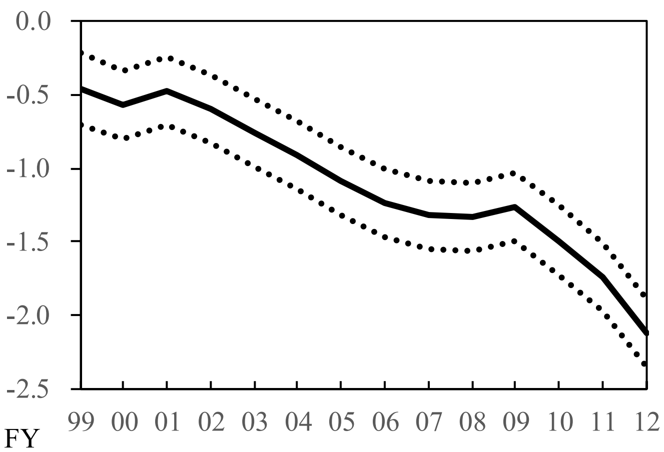
Figure 8: Number of Patents Relative to R&D Investment



Sources: Development Bank of Japan; Institute of Intellectual Property, "IIP Patent DB;" PatentSquare; Patent Office.

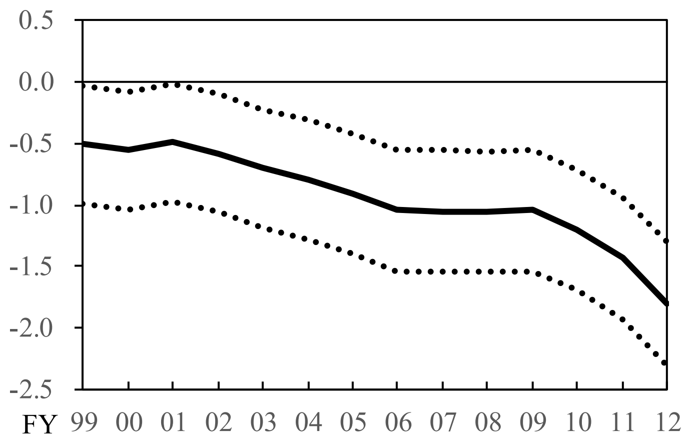
Note: The figure shows the averages for firms listed on the first and second sections of the Tokyo Stock Exchange.

Figure 9: Year Fixed Effects in the Innovation Function



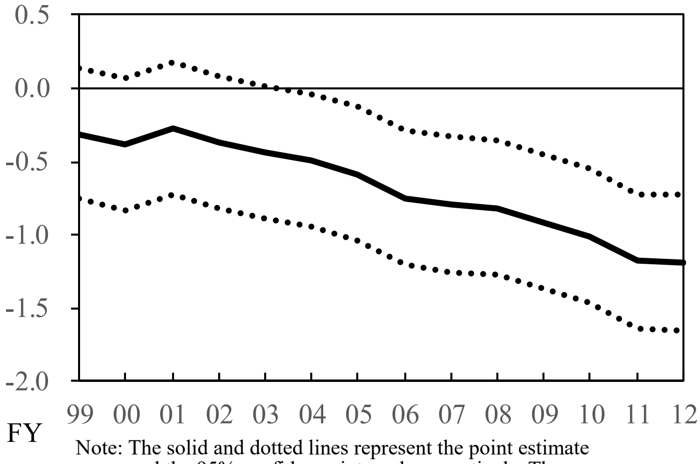
Note: The solid and dotted lines represent the point estimate and the 95% confidence interval, respectively. The figure shows the estimation results for the innovation function where the dependent variable is the citation flow.

Figure 10: Year Fixed Effects in the Innovation Function with Firm Fixed Effects



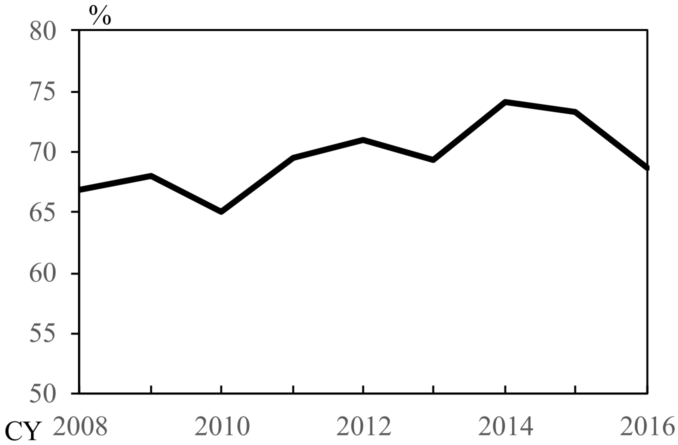
Note: The solid and dotted lines represent the point estimate and the 95% confidence interval, respectively. The figure shows the estimation results for the innovation function where the dependent variable is the citation flow.

Figure 11: Year Fixed Effects for the Innovation Function with Adjusted Citation Stock



Note: The solid and dotted lines represent the point estimate and the 95% confidence interval, respectively. The figure shows the estimation results for the innovation function where the dependent variable is the citation flow.

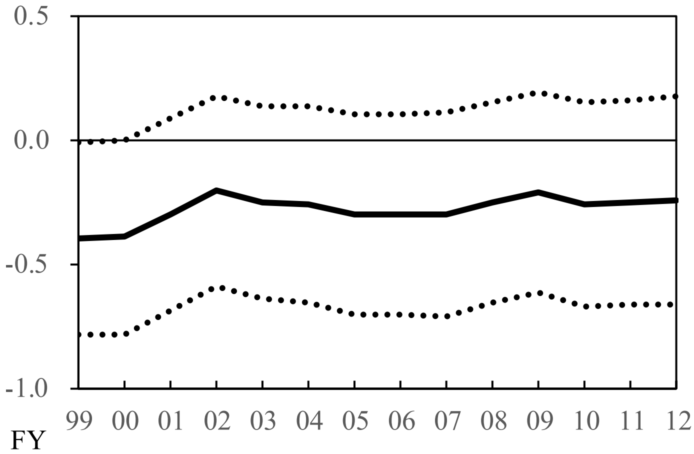
Figure 12: Ratio of the Number of Patent Applications to the Number of Inventions



Source: Patent Office.

Note: The number of inventions is the number of inventions reported to the department responsible for a firm's management of intellectual property rights regardless of whether a patent application has been filed.

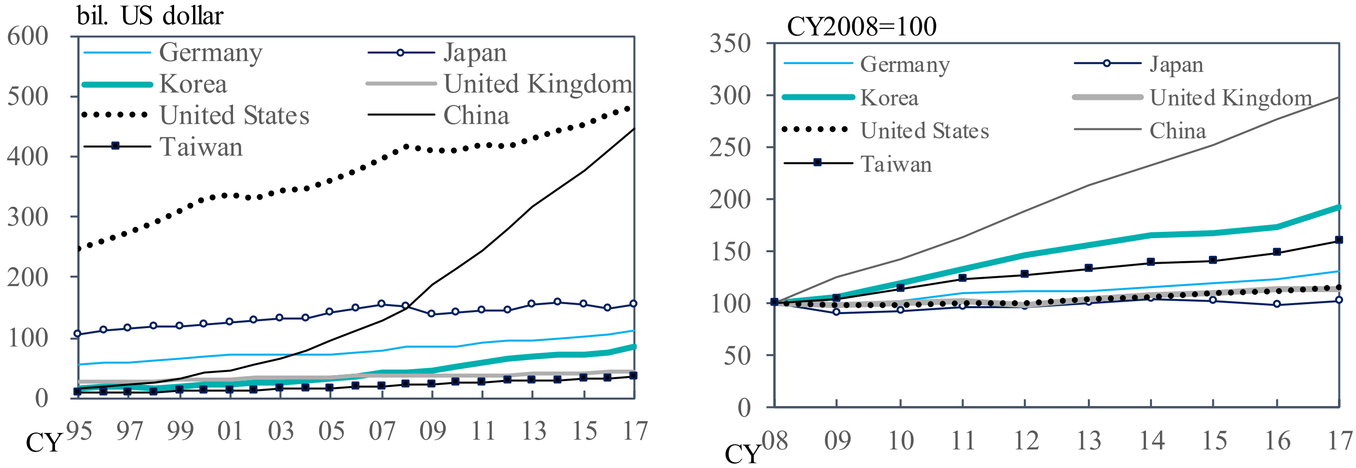
Figure 13: Year Fixed Effects for the Patent Registration Function



Note: The solid and dotted lines represent the point estimate and the 95% confidence interval, respectively. The figure shows the estimation results for the patent registration function where the dependent variable is the patent registration flow and the explanatory variables are same as those in Table 4.

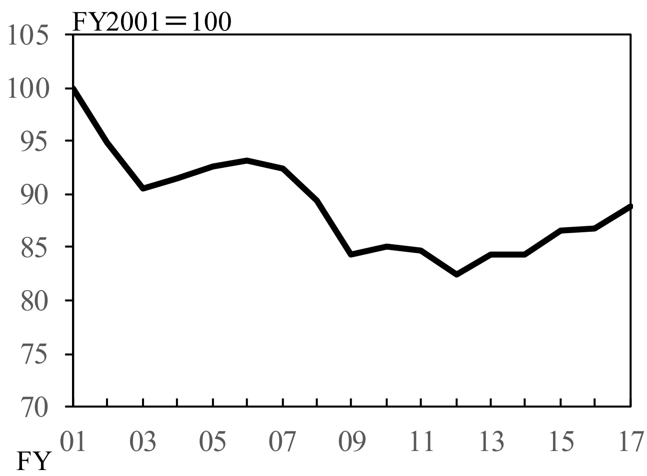
Figure 14: R&D Investment by Country

Level — Since 2008



Source: OECD.

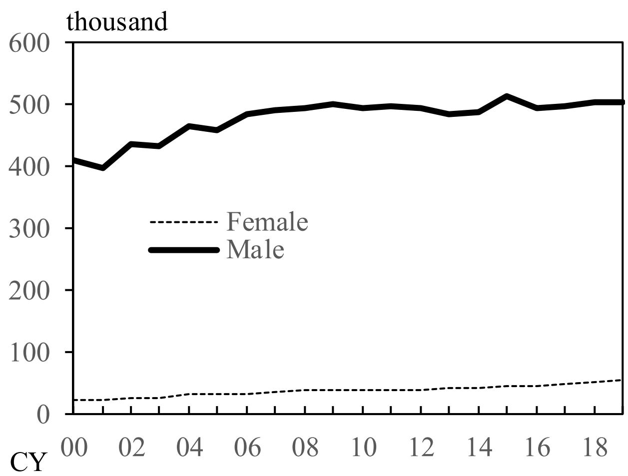
Figure 15: Personnel Expenses per Researcher



Source: Ministry of Internal Affairs and Communications, "Report on the Survey of Research and Development."

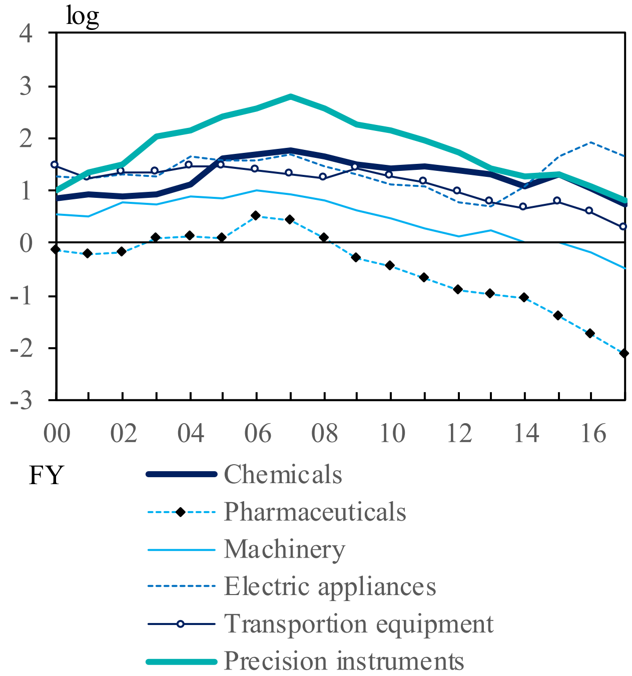
Note: Personnel expenses per researcher = Personnel expenses in R&D expenditure / Number of researchers.

Figure 16: Number of Researchers in Japanese Firms



Source: Ministry of Internal Affairs and Communications, "Report on the Survey of Research and Development."

Figure 17: Patent Stock in New Fields



Sources: Development Bank of Japan; Institute of Intellectual Property, "IIP Patent DB;" PatentSquare; Patent Office.
Note: The figure shows the averages for firms listed on the first and second sections of the Tokyo Stock Exchange.

Table 1: Productivity and Citation and R&D Stocks

	(1) log(GrossValue)	(2) log(GrossValue)	(3) log(GrossValue)	(4) log(GrossValue)
log(Capital)	0.112**	0.0819*	0.0692	0.114**
	(0.0515)	(0.0479)	(0.0500)	(0.0532)
log(Labor)	0.589***	0.528***	0.512***	0.494***
	(0.0491)	(0.0542)	(0.0575)	(0.0498)
log(R&DSTOCK)	0.0546*		0.0637**	0.0175
	(0.0309)		(0.0313)	(0.0258)
log(CITESTOCK)		0.0187**	0.0162*	0.0139**
		(0.00879)	(0.00876)	(0.00580)
N	8198	7936	7598	7598
Firm Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	–
Industry × Year Fixed Effect	No	No	No	Yes

Notes: Standard errors in parentheses. The table shows the estimation results for the production function where the dependent variable is gross value added. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Citation Stock and Productivity from the JIP Database

	(1) Citation Stock	(2) R&D Stock
Explanatory variablesΔlog(CITESTOCK)	0.0395**	
	(0.0181)	
Δlog(R&DSTOCK)		0.0290
		(0.0629)
N	318	208

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. The table shows the estimation result for the equation where the dependent variable is the the growth rate of productivity from the JIP database. Note that the JIP Database is the most widely used database in academia for analyses of Japanese TFP. Due to data limitations, the estimation period for (1) is FY 1997-2015, while that for (2) is FY 2003-2015. However, the results remain qualitatively unchanged when we use observations for FY 2003-2015.

Table 3: Production Function with Adjusted Citation Stock

	(1)
	log(GrossValue)
log(Capital)	0.115**
	(0.0533)
log(Labor)	0.494***
	(0.0497)
log(R&DSTOCK)	0.0170
	(0.0258)
log(CITESTOCKAD)	0.0127**
	(0.00639)
N	7593
Firm Fixed Effect	Yes
Industry $\times$ Year Fixed Effect	Yes

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. The table shows the estimation result for the production function where the dependent variable is gross value added. CITESTOCKAD represents the adjusted citation stock.

Table 4: Estimation Results for the Innovation Function

	(1)n=0 log(CITEFLOW)	(2)n=2 log(CITEFLOW)	(3)n=5 log(CITEFLOW)
log(R&D$_t$)	0.307***	0.123*	0.167*
	(0.0190)	(0.0682)	(0.0876)
log(R&D$_{t-1}$)		0.162*	0.109
		(0.0902)	(0.123)
log(R&D$_{t-2}$)		0.0273	-0.0947
		(0.0607)	(0.112)
log(R&D$_{t-3}$)			0.0389
			(0.112)
log(R&D$_{t-4}$)			0.128
			(0.104)
log(R&D$_{t-5}$)			-0.0349
			(0.0732)
Sum of the coefficients on R&D$_{t-j}$		0.312***	0.313***
N	6403	5400	3949
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. The table shows the estimation results for the innovatoin function where the dependent variable is the citation flow. R&D represents real R&D investment.

Table 5: Industry Fixed Effects in the Innovation Function

	(1)n=0 log(CITEFLOW)
Pharmaceuticals	-1.363***
	(0.0805)
Machinery	-0.0817**
	(0.0393)
Electric appliances	0.339***
	(0.0383)
Transportation equipment	-0.625***
	(0.0454)
Precision instruments	0.139**
	(0.0580)
N	6403

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. The table shows the the estimation results for the industry fixed effects, setting the chemical industry as the reference category and using the innovation function with n=0 in Table 4, where the dependent variable is the citation flow.

Table 6: Firm Age and Patent Flow in New Fields

	(1) log(NewPatFlow)
log(Age)	-0.229*
	(0.128)
ROA	-1.962**
	(0.934)
log(TotalAssets)	0.341***
	(0.0565)
SalesGrowth	0.377
	(0.232)
log(CITESTOCK)	-0.135***
	(0.0394)
N	851
Industry Fixed Effect	Yes
Year Fixed Effect	Yes

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.
The table shows the estimation results for the model examining the patent flow in new fields. The explanatory variables include the firm age (AGE), total assets (TotalAssets), and sales growth (SalesGrowth), and all variables are lagged by one year. The estimation period is FY 2008-2012.

Table 7: Patent Stock in New Fields and Innovation

	(1) log(CITEFLOW)
log(NewPatStock)	0.0561***
	(0.0167)
log(RSALES)	0.170***
	(0.0600)
log(R&D)	0.159***
	(0.0435)
N	6263
Firm Fixed Effect	Yes
Year Fixed Effect	Yes

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. The table shows the estimation results for the innovation model for firms in the six manufacturing industries. RSALES represents real sales and R&D represents real R&D investment. To address potential endogeneity issues, we lag the patent stock in new fields (NewPatStock) by three years.