REVIEW:

Scientific research and research collaboration may remedy slowed innovation in Japan due to diminishing returns to knowledge

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Abstract

New knowledge is an important input for innovations. The knowledge production model of innovations considers the return to knowledge to be constant because of knowledge spillover. However, some studies have found that innovations slow down over time, as the return to knowledge diminishes. A number of technological indicators, discussed here, support the proposition that scientific research and collaborative research are potential remedies for the diminishing returns to knowledge. However, differences are found in the trends of scientific research and collaborative research between Japan and the US. The widening gap in technology indicators between the two can be attributed to the relatively lower level of scientific and collaborative research in Japan.

Keywords: Japan, innovation, knowledge, productivity, scientific research
JEL code: O31, O32

Introduction

Innovation is an essential factor for technological advancement and productivity growth. There is some evidence that innovation in Japan has been sluggish and the gap between various technology indicators in Japan compared to those in the US and other industrialized economies seems to be widening in recent years. In the late 1990s, the US enjoyed a strong recovery in productivity gain, partly due to its massive expansion in new technological fields such as information technology and biotechnology. Japan, on the other hand, appears to have kept lagging behind in these new technologies. For example, in terms of innovative activities or productivity, Japan gained little momentum throughout the same period. Some evidence suggests that innovative capacity might have even declined in Japan. Contrasting trends between Japan and the US seem puzzling: why does one suffer from sluggish technological performance, while the other enjoys a strong gain? And how can Japan accelerate the performance in innovations?

This review further proposes two potential remedies to this situation, facilitating scientific research and research collaboration. In recent years, interaction between science and technology has become more important than ever, as research and development (R&D) increasingly requires scientific knowledge. Likewise, research collaboration among firms has been a popular practice. In this study, we will focus on the role of scientific research and research collaboration in enhancing knowledge spillover. The model of knowledge production asserts that knowledge spillover is a key factor behind sustained technological advancement. We propose that scientific research and collaboration in research are the keys to enhancing knowledge spillover and strengthening innovative capacity.

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Methodology

This study is based on a review of the literature on various growth theories and innovation, delving into the theories in the fields of economic growth, innovations, and applied economics. It explores the factors that have the potential to accelerate innovative activities.

Models of semi-endogenous growth assert that innovative activities may slow down over time. The rationale behind their argument is diminishing returns to knowledge; i.e. as the economy accumulates the stock of knowledge, creation of new knowledge becomes increasingly difficult. In innovation literature, there are arguments that support the concept of diminishing returns to knowledge. However, the links between the theories in innovation literature and semi endogenous growth models have not been discussed extensively.

This review thus attempts to clarify the linkage between them, and seek for potential factors that can overcome the diminishing returns.

Findings and Discussion

Productivity and innovation in Japan: Productivity gains in many industrialised countries were sluggish throughout the 1970s and 1980s. Since the 1990s, however, this trend has been reversed in many countries. In particular, the US enjoyed a strong improvement in productivity in the late 1990s and 2000s. However, productivity in Japan did not improve during the same period (Figure 1).

Indeed, some studies point out that innovative capacity in Japan has been declining. Studies by Branstetter and Nakamura (2003), and the National Institute of Science and Technology Policy (2003) find some evidence that R&D in Japan has been less productive.

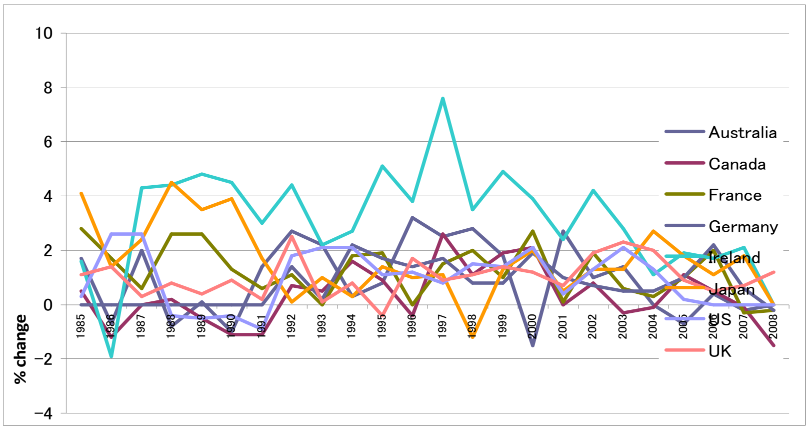


Figure 1. Multi-factor productivity in selected OECD countries (Source: stats. OECD)

Recent studies also show a worrying trend of slowing down of technological progress in Japan. Branstetter and Nakamura (2003) write with alarm that "the implications of the apparent decline in Japanese innovative capacity are potentially quite serious for Japan's long-run economic prospects." (Branstetter and Nakamura, 2003, p.3)

Table 1 (a and b) shows the estimated total factor productivity (TFP) growth, which is an indicator of the overall technological change, using data from various studies. As seen in the table, most studies show a noticeable slowdown in TFP growth in the 1990s. According to growth accounting studies by Yoshikawa

(2000), TFP growth during the 1990s dropped to nearly 0%, in contrast to 3.7% in the 1960s. Sato (2002) argues that the non-manufacturing sector has suffered the most from TFP decline, with the decline in TFP in the manufacturing sector being modest. Manufacturing sector's TFP growth in 1990s was 2.2% compared to 2.6% in the 1980s. In contrast, the non-manufacturing sector's TFP growth dropped to 0.3% from 1.8% in the same period.

Table 1. Japanese and US TFP

a. Japanese TFP as reported in various studies

Author(s)	1970s	1980s	1990s
Otani *et al* (2004)	N/A	1.8	0.6
Miyakawa (2003)	N/A	1.6	0.8
Yoshikawa (2000)	0.7	1.0	0.0
Kawamoto (2004)	3.0	2.3	2.1

b. US TFP in various studies

Author(s)	1970s	1980s	1990s
Bernstein and Mohen (1994)	-0.4 (1975-79)	-2.4 (1980-1985)	N/A
Jorgenson *et al* (2003)	N/A	-0.08	0.63

The slowdown in innovations is not limited to TFP, but can also be seen in patenting. As Figure 2 shows, the gap in the number of patents per researcher widened during the 1990s. Although the gap between the US and Japan seemed to be closing in the late 1990s, there is still a considerable gap between the two countries, which suggests that innovative activity in Japan has become less productive. Kondo (1999) has analysed the effectiveness of R&D activities by estimating the 'patent production function'. The results show that the productivity of Japanese innovative activities has been deteriorating since the mid-1980s. Using a similar methodology, Branstetter and Nakamura (2003) estimated the knowledge production function using patent data between 1982 and 1997. Their results indicate a downward trend in patenting, even after controlling for R&D inputs and propensity to patent. Their results suggest that the slowdown in Japanese innovative activities is not likely to be the result of lower R&D efforts, or a shift in the propensity to patent, but rather that Japanese innovative capacity itself has been declining because of R&D becoming less productive.

Some other technological indicators also confirm this perspective. The OECD Science and Technology Database shows the widening gap in technology exports between Japan and other major industrialised countries. Compared to the US where a massive increase in technology exports started in the late 1980s, Japanese figures started to increase only after the mid 1990s. More strikingly, the exports-to-imports ratio in high-tech industries in Japan has dropped sharply in the last two decades (Figure 2).

The General Index of Science and Technology (GIST), an indicator developed by the National Institute of Science and Technology Policy (NISTEP) also suggests a slowdown in Japanese innovation performance. Figure 3 shows that the GIST output indicator for Japan has increased only modestly in the last 20 years, while the US figure shows a dramatic increase in technology outputs (NISTEP, 2003). While innovation performance in Japan seems to have been slowing down in recent years, research inputs in Japan have been consistently rising. Moreover, both R&D expenditures and R&D personnel have been increasing steadily, which suggests that the slowdown in Japanese innovation, as Branstetter and Nakamura (2003) claim, is likely to be due to a decline in R&D productivity.

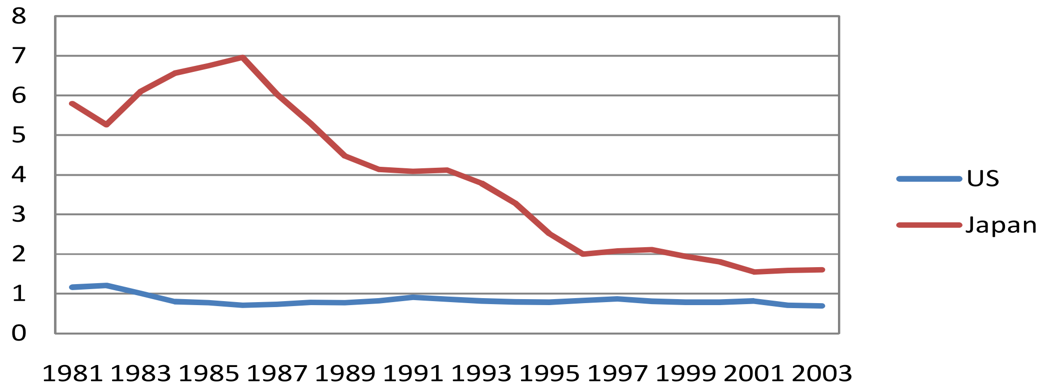


Figure 2. Export-import ratio in high tech industries. (Source: OECD Science and Technology Indicator database)

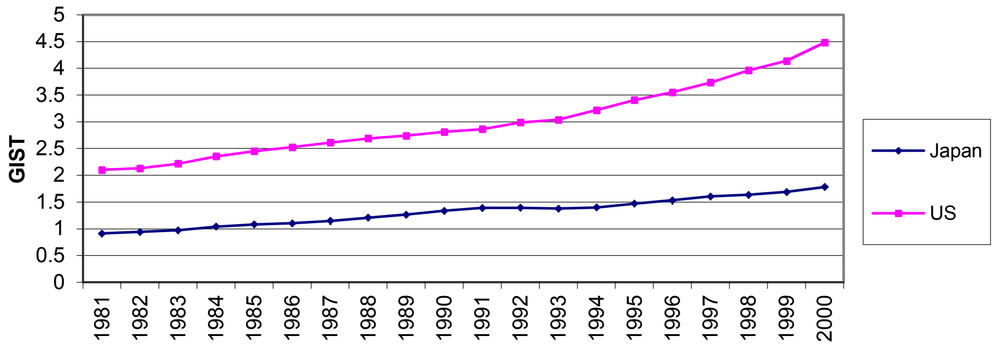


Figure 3. General Indicator of Science and Technology (GIST) (Source: NISTEP, 2003)

Knowledge production, knowledge spillover, and return to knowledge: Why has Japan been suffering from a loss in innovation capacity while the US enjoyed strong improvement in this area in the late 1990s? To answer this question, we pay particular attention to the *return to knowledge*. Knowledge created from prior research can be utilised in current research. Therefore, the cumulative stock of knowledge from prior research can be considered an important input for innovation. In turn, the return to the stock of knowledge is an important determinant of innovative capacity.

Griliches (1979), one of the pioneering researchers of *knowledge production*, argues that the aggregate output level of the economy depends on conventional inputs (such as capital and labour) plus *knowledge capital*. In other words, *knowledge capital* may be considered as another form of production input. Griliches (1979, 1990, 1992) argues that knowledge production depends not only on current R&D level, but also on cumulative knowledge from past R&D, and asserts that knowledge production is a function of cumulative stock of R&D investment. Griliches has emphasised the importance of *knowledge spillover*, i.e. the stock of knowledge has a positive external effect.

Many studies including Romer (1990) assume that knowledge production operates at a constant return to knowledge stock. This assumption is justified because of the nature of knowledge as an input. The underlying concept is the public-good nature of knowledge: non-rivalry and the (quasi) non-excludability

(Romer, 1990, section II). As technological knowledge can be used by many agents simultaneously, knowledge can be accessed and utilised by anyone in the economy. Griliches (1979, 1995) also points out that knowledge can be considered as a special kind of input, in that unlike other forms of inputs, it is not subject to diminishing returns.

The public-good nature of knowledge, in turn, facilitates *knowledge spillover*. The endogenous growth theory shows that *knowledge spillover* is the key factor in achieving sustained economic growth. Due to such a spillover effect, knowledge is not subject to diminishing returns. Romer (1990, p.75) argues that knowledge (as a non-rival input) can be accumulated without a boundary and that this leads to a constant return to knowledge production.

Diminishing returns to knowledge: Jones (1995a, 1995b) has criticised the assumption that knowledge does not face diminishing returns. Jones' criticism is based on the empirical observation that technological progress (measured by TFP and the number of patent applications) in the major industrialised countries has not been accelerating despite a considerable increase in R&D efforts in most of these countries. Jones argues that knowledge spillover does not assure sustained technological progress, because knowledge spillover is offset by negative externalities. In Jones' model, the return to knowledge is less than one, indicating that accumulation of knowledge stock does not lead to a proportional increase in new knowledge.

Whether the return to knowledge is constant or diminishing is an extremely important question. If the return to knowledge is diminishing, it implies that technological advancement eventually slows down. There are several potential impediments to knowledge spillover. In the present study, we focus on two impediments which are commonly recognised in literature: fishing-out that arises from exhaustion of technological opportunities, and fragmentation of knowledge that arises from technological heterogeneity.

Fishing-out and diminishing returns to knowledge: One of the reasons why the return to knowledge may decrease is the fishing out of technological opportunities. That is, innovating new products increasingly becomes more difficult, and the opportunities for further innovations are likely to decrease. The concept of fishing out is based on a *search model* of innovation, which appeared in the 1970s. The search model implies that innovators tend to exploit their technological opportunities from innovations that are seemingly easy to produce. As the technological level rises, the technological opportunities exhaust, making consequent innovations increasingly more difficult (Evenson and Kislev, 1976).

One may assume that the opportunity for creating new knowledge acts as rivalry over an exhaustible resource. In other words, knowledge production requires non-rival knowledge capital and rival technological opportunities as inputs. As the technology level rises, the opportunity for further technological progress would eventually be exhausted. Jones (1995a) has suggested that this may be due to negative externalities from fishing-out, and duplicating R&D efforts. Segerstrom (1998) and Kortum (1997) argue that the threshold quality for successful innovation rises with the technology level, and therefore the probability of successful innovation diminishes.

Diminishing returns due to fragmentation of knowledge: Another group of studies focuses on the *fragmentation* of knowledge, i.e. the heterogeneity of technology can be an impediment of knowledge spillover. Some studies including those by Peretto and Smulders (1998, 2002), Dinopoulos and Thompson (1998, 1999), and Young (1998), have focused on technological heterogeneity. These studies find that knowledge spillover takes place within an industry, but not among industries. The underlying concept is that technology is heterogeneous and path-dependent, and therefore knowledge from unrelated industries cannot contribute. The studies mentioned above find that technological progress slows down when knowledge is divided and fragmented into small pieces. As the economy grows, the knowledge is fragmented into a number of small networks. Knowledge spillover tends to be local (within fragmented networks), and fades away with technological distance.

One of the reasons why fragmentation of knowledge occurs is tacitness of knowledge (Foray, 2004; Antonelli, 2001). While some knowledge is codified (e.g., patents, scientific articles, manuals etc.), many proportions of knowledge are tacit, embedded in internal experience and learning (Antonelli, 2001). Foray (2004) further argues that firms may purposely leave knowledge tacit, as a way of controlling intellectual property rights. When knowledge is tacit, knowledge spillover is limited, and tends to be local, because such a communication is likely to take place within an industry (or industries with a common technology).

Another factor that influences the fragmentation of knowledge is the complementarities among technologies. Technology comprises complex systems that are related to each other, and the technological complementarities reflect such inter-relations among technologies. As Foray (2004), Carlaw and Lipsey (2002), and Lipsey, Baker, and Carlaw (1998) emphasise, technologies are rarely stand-alone, but are more often components of other technological systems. Such systems can be considered equivalent to local technological clusters (or spillover networks) wherein technological complementarities play a vital part in their formation. Lipsey *et al*. (1998) and Antonelli (2001) argue that a local network (they call it main technology) is formed by complementarities among technologies (sub-technologies in their writing).

When two technologies are apart, it is likely, though not necessarily so, that the complementarities between them are low. For example, technology in the pharmaceutical industry has little to do with the electronics industry. As technological level rises, it is likely that technology is increasingly divided into small specialised networks, and therefore the spillover effect is likely to be confined within specialised spillover networks.

Knowledge production in Japan: is the return to knowledge diminishing?

Although it is difficult to measure the return to knowledge, one can find some evidence of diminishing returns from patent data. Figure 4 shows the number of backward citations per patent. Backward citations occur whenever a patent refers to the technology used in other patents granted in the past. Therefore, backward citations can indicate how a patent has utilised the knowledge from previous innovations.

As Hall, Jaffe and Trajetenberg (2001) point out, backward citations may contain the trail for knowledge spillover. In this sense, the number of citations per patent can indicate the amount of knowledge used as input. As the graph shows, the number of citations per patent has been increasing throughout the last three decades. Assuming that the citations represent knowledge as input, it seems that more knowledge is required to invent one new patent.

Examining data on patent claims can provide further evidence because they specify the details of patented innovation that is not previously cited. The number of claims can indicate the scope of patented innovation (Hall et al., 2001), or the technological significance of the innovation. The higher the number of claims, the more new technologies the patent contains. A patent with more claims is likely to be technologically more significant. Figure 5 shows the average number of claims per dollar of R&D expenditures. As the graph shows, the number of claims per dollar has dropped since the 1980s.

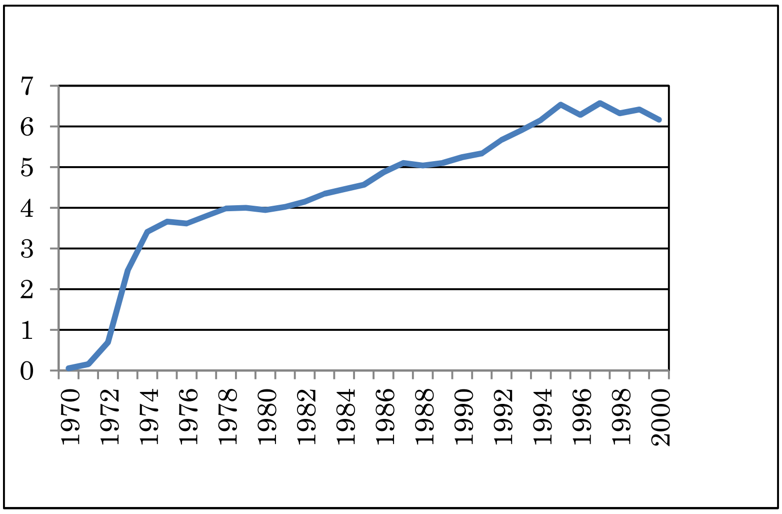


Figure 4. The number of backward citations per patent in Japan
(Source: NBER Patent Database and Source: OECD Science and Technology Database)

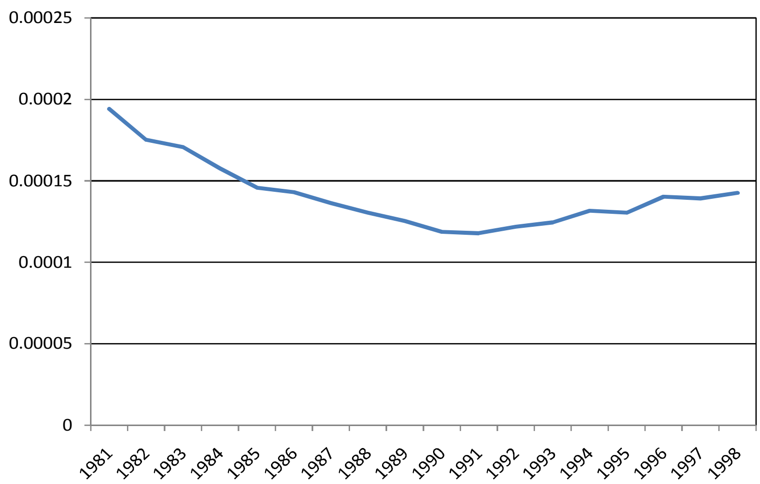


Figure 5. Average number of claims per dollar of R&D expenditures in Japan
(Source: NBER Patent Database and Source: OECD Science and Technology Database)

Overcoming diminishing returns to knowledge: In the previous section, we argued that diminishing returns to knowledge can be attributed to a fragmentation of knowledge and/or fishing out of technological opportunities. One may ask how diminishing returns could be overcome and innovation capacity rejuvenated? We shall examine how scientific research and research collaboration may be potential remedies.

Science and expansion of technological opportunities: It is commonly believed that a radical technological breakthrough is needed when innovation slows down; such a technological breakthrough can facilitate a massive wave of innovations. The recent boom in information technology (IT) and bio-technologies can be considered as typical cases. This perspective is common in a wide range of studies. Mokyr (1991) introduces the concept of *macro-invention* (as opposed to *micro-invention*), and Rosenberg (1994) distinguishes *major innovation* from *minor innovation*. Major or macro invention is a radical breakthrough, and minor or micro innovation is a more incremental technological change. They argue that the arrival of macro innovation is followed by a rapid increase in micro innovations.

A similar concept has also been introduced to the growth theory. The model of *general purpose technology* (GPT) by Helpman and Trajtenberg (1998) incorporates a paradigm shift from radical technological breakthrough. These authors have extended the endogenous growth model, such that the arrival of new GPT creates an entirely new wave of technological advancement. When a new GPT is introduced, technological advancement accelerates, as the new GPT creates opportunities for compatible innovations. Their study shows that the economy may experience cyclical acceleration and deceleration of technological advancements.

By the same token, Olsson (2005) explicitly shows that radical innovation can expand technological opportunities and accelerate economic growth. Olsson finds that diminishing returns may be overcome by exploiting the hidden technological opportunities in scientific discoveries and that technological breakthrough occurs endogenously. When the economy suffers from diminishing returns to knowledge, economic agents try to expand technological opportunities by conducting basic research. One of the important features in Olsson's model is inclusion of basic research. He argues that basic research can expand technological opportunities by filling the gap between applied research and scientific discoveries.

The important question is the mechanism how such technological breakthrough may occur. One of the possible answers is science. Rosenberg (1994) and Mokyr (1991) argue that scientific advancement can contribute via arrival of breakthrough inventions. Foray (2004) highlights that the contribution of science can take place via: (i) a more systematic and effective base for discovery and innovation; (ii) better control (quality, impact, regulation) of the newly introduced products and processes; and (iii) creating entirely new products or processes. Evenson and Kislev (1976) find that science can improve the ability to explore potential technologies. The idea that science contributes to accelerating technological progress has been applied to growth literature too. Li (2000) and Olsson (2005) both have demonstrated that scientific knowledge is essential for overcoming diminishing returns in R&D.

The recent expansion of information technology and bio-technology are prime examples that technological innovation increasingly requires scientific knowledge. Figure 6 shows the share of basic research in business sector research expenditures (BERD). During the 1990s, industry sectors in the US expanded their efforts in fundamental scientific research. At the same time, the linkage between industry and universities strengthened. Japan has been behind in this trend. It was in early 2000s that the Japanese government started encouraging joint research between industries and universities

Figure 7 shows the 'science linkage' in the US and Japan. The science linkage measures the citations flow between patents and scientific papers. As the graph shows, the science linkage in the US has dramatically risen since the early 1990s. As the National Institute of Science and Technology Policy (NISTEP) emphasises, a strong linkage between universities and industries may provide an explanation for the surge of R&D performance in the US in the 1990s.

Figure 8 (a, b) shows the correlation between spending on basic research and the science linkage in Japan and in the US, respectively. The graphs show a clear positive relationship between basic research and science linkage, which indicates that basic research facilitates the diffusion of scientific knowledge to industries.

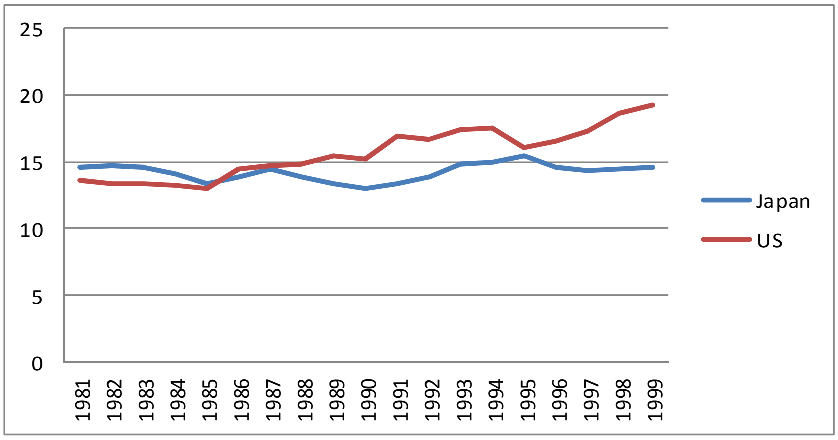


Figure 6. Percentage of basic research in business-sector research expenditures. (Source: OECD Science and Technology Database)

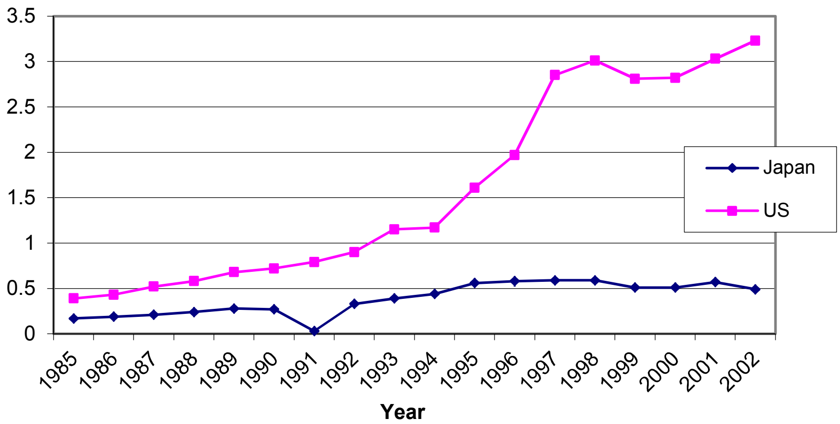


Figure 7. The science linkage. (Source: NISTEP, 2004)

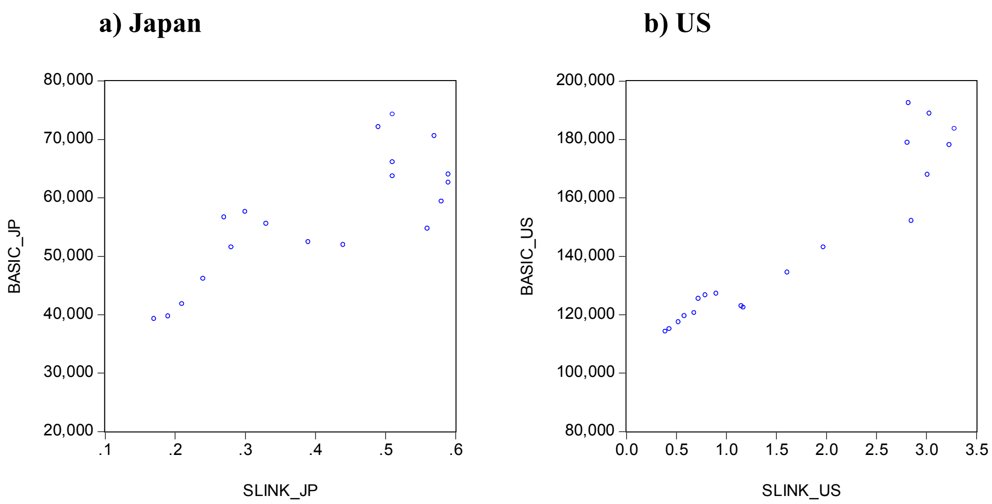


Figure 8. Basic research and science linkage [Sources: NISTEP (2004); OECD Science and Technology Database]

Research collaboration combines fragmented pieces of knowledge: Another way to overcome diminishing returns in R&D is *defragmentation* of knowledge. In other words, by exploring the hidden complementarities among seemingly-different technologies, one can enhance knowledge spillover. As discussed before, knowledge spillover is influenced by complementarities among different technologies. Knowledge spillover is absent (or very weak) across technologies that are not complementary to one other. Complementarities among different technologies lead to the appearance of modules or networks of technologies in which knowledge spillover takes place only within the network (Antonelli, 2001; Perreto and Smulder, 2002). Therefore, inter-firm and inter-industry knowledge spillover is likely to be limited outside of such a network.

It is argued that if an economy expands the network of knowledge-sharing, it is possible to combine fragmented knowledge and enhance knowledge spillover. By establishing collaborative relationships, fragmented knowledge can be shared and combined together. In this process, firms and industries are required to combine their specialised knowledge into more generic knowledge. Foray (2004) identifies 'coordination' or 'integration' activities, which aim to standardise specialised and localised knowledge. By the same token, various studies, including those by Morosini (2002), Antonelli (2001), and Patrucco (2004), have introduced the concept of *collective knowledge*. The studies on collective knowledge point to the importance of collaboration. Firms coordinate with each other, creating a joint research effort that works toward integrating tacit and fragmented knowledge. Antonelli (2002) argues that the efforts to create collective knowledge can lead to exploitation of implicit complementarities among localised technologies.

Collective knowledge creation is the act of converting specialised knowledge into *generic* knowledge. There have been a number of studies that suggest a similar conceptualisation. Foray (2004) argues that generic knowledge expands the complementarities among technologies and thereby rejuvenates the knowledge production process. As Foray (2004) argues, when an economy faces diminishing returns to knowledge, firms coordinate with each other and collectively create generic knowledge. By collaborating, they can convert firm/industry specific knowledge into generic knowledge which can be used in other industries. Research collaboration also helps with the diffusion of tacit knowledge. Needless to say, collaboration enables researchers across industries to communicate directly and share their knowledge and expertise, and it may thus facilitate transferring tacit knowledge from one industry to another.

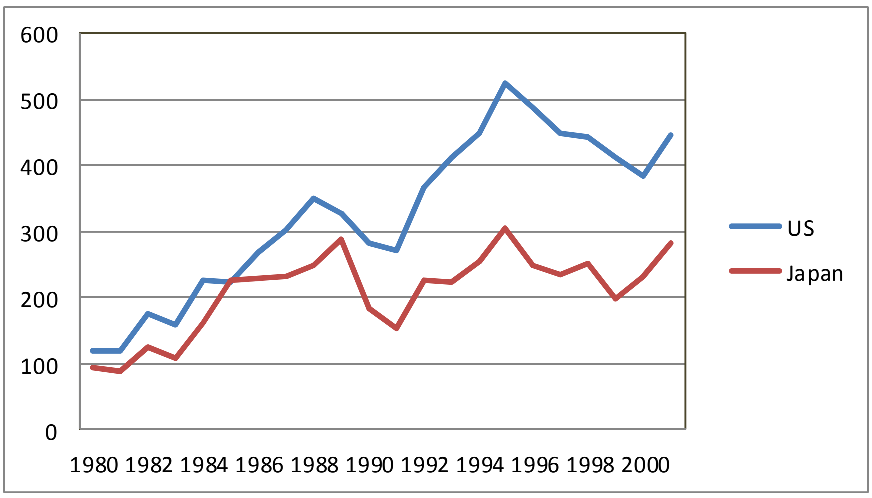


Figure 9. Number of research alliances in the US and Japan (Source: The National Science Foundation, US)

The importance of collaborative research has been rising. Firms in many industrialised countries have been increasingly engaged in joint research in one way or another. Figure 9 shows the number of research alliances in Japan and the US. As the graph indicates, US firms have been expanding the number of their alliances since early 1990s. Research collaboration seems to be taking place in fast-growing areas, including IT and biotechnology (Figure 10). The widening gap in technology between Japan and the US at least in some extent can be attributed to the fact that Japan has been lagging behind in these fast growing areas.

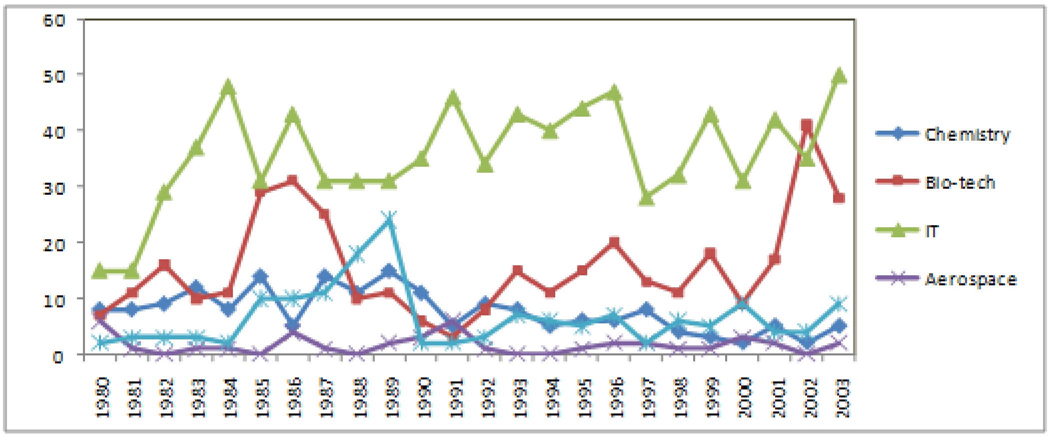
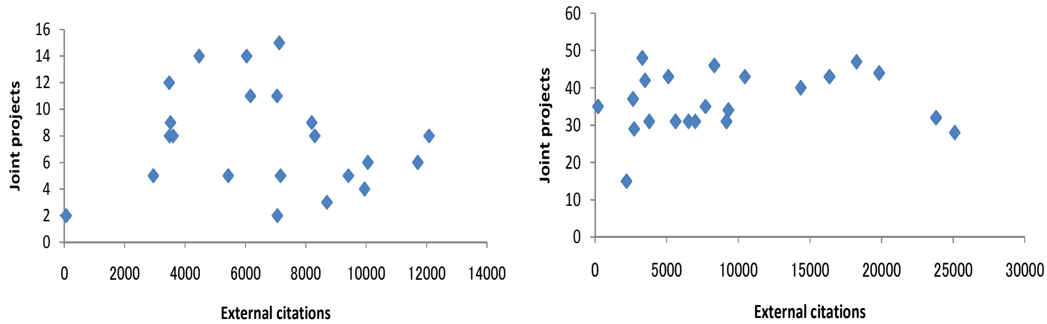


Figure 10. The number of major joint research projects (Source: National Science Foundation)



a: chemistry **b:** IT

Figure 11. The number of external citations and the number of major joint research projects

Figure 11 (a, b) includes scatter diagrams of external citations and the number of major joint projects. While some technological fields (especially IT) show a clearer relationship, other technological fields do not indicate a clear relationship between the two variables.

Conclusion

In recent years, innovations in Japan seem to be lagging behind those in the US. Why has the performance of Japanese innovations been sluggish? This paper has tried to address this question by focusing on the returns to knowledge. While the model of knowledge production assumes that return to knowledge is constant, many studies find that the return to knowledge is likely to diminish. Many of existing studies point to fishing out of technological opportunities and fragmentation of knowledge as the reasons for this trend. This study has proposed that scientific research and collaborative research are the key factors to overcome the diminishing returns to knowledge. We have reviewed various studies on how scientific research and collaborative research influence knowledge production. Many studies find that scientific research and collaborative research can be effective remedies for diminishing returns. A number of technological indicators support our proposition. Comparing the trends of scientific research and collaborative research in Japan to those in the US provides noticeable differences. (Basic) scientific research in the US increased dramatically in the 1990s, while that in Japan was subdued. In the US, patents increasingly cite scientific papers, suggesting that scientific knowledge played a larger role in technological innovations.

Similarly, the firms' joint researches have increased considerably in the US. There seems to be a strong correlation between knowledge spillover and collaborative research; measuring knowledge spillover by patent citations clearly demonstrates that collaborative research enhances knowledge spillover. Since collaborative research takes place in fast-growing technological fields, one can argue that research collaboration has turned into an increasingly important determinant of innovative performance.

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