2C17 Impacts of Functionality Development on Dynamism between Learning and Diffusion of Technology

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Under a long lasting economic stagnation, since significant increase in R&D investment has become difficult, practical solution could be found in systems approach maximizing the effects of innovation as a system by making full utilization of potential resources of innovation. At the same time, under the increasing significance of information technology (IT) in an information society, which emerged in the 1990s, functionality development has become crucial for stimulating a self-propagating nature of IT driven innovation.

Stimulated by these understandings and prompted by a concept of institutional innovation, this paper attempts to analyze the interacting dynamism of innovation in a comprehensive and organic system. Theoretical analysis and empirical demonstration are attempted focusing on dynamism between learning and diffusion of technology taking Japan's PV development, which follows the similar trajectory of IT's functionality development, over the last quarter century.

1. Introduction

While technological innovation plays a significant contribution to socio-economic development, under a long lasting economic stagnation, the stagnation of technology development has become a crucial structural problem common to all advanced countries. Similarly, Japan has been suffering from a collapse of its long lasting virtuous cycle between technology development and economic growth leading to a vicious cycle between economic stagnation and the stagnation of R&D investment. Under such circumstances, significant increase in R&D investment has become difficult requirements that increases the significance of the systems approach maximizing the effects of innovation as a system. At the same time, under the increasing significance of information technology (IT) in an information society which emerged in the 1990s, functionality development has become crucial for stimulating a self-propagating nature of IT driven innovation.

Prompted by these understandings, this paper attempts to analyze the interacting dynamism of innovation in a comprehensive and organic system. Innovation is recognized as a very subtle entity subject to conditions of institutional systems. Therefore, theoretical analysis and empirical demonstration are attempted focusing on a dynamism between learning and diffusion of technology taking Japan's PV development over the last quarter century. PV development trajectory is taken as it follows the similar trajectory of IT's functionality development.

Section 2 attempts to analyze the dynamic behavior of learning coefficient by constructing a mathematical model and empirical demonstration. Section 3 links learning and diffusion of technology by developing this mathematical model. Section 4 provides an interpretation of these analyses by elaborating an institutional dynamism. Section 5 briefly summarizes the findings.

2. Dynamic Behavior of Learning Coefficient

Operating in competitive markets makes individuals, firms, industries and nations do better. This motivation is at the heart of the learning exercise phenomenon and subsequent learning effects. Price is the most important measure of performance for this motivation and returns of consequent cumulative efforts, generally expressed by cumulative production.

Thus, learning effects can be captured by the following equation:

$$P = B \cdot Y^{*-\lambda} \tag{1}$$

where P: prices, B: scale factor; $Y^* = \sum Y$: cumulative production (Y: production); and
λ (> 0): learning coefficient.

In case of innovative goods, prices can be depicted by a function of time t

$$P = B' e^{-\eta t} \tag{2}$$

where B': scale factor; η: coefficient; and t: time trend.

Trajectory of diffusion process of Y^* can be depicted by the following epidemic function:

$$\frac{dY^*}{dt} = bY^*(1 - \frac{Y^*}{K}) \quad (3)$$

where b: coefficient; and K: carrying capacity.

Provided that diffusion process of Y^* follows a trajectory depicted by a logistic growth function within a dynamic carrying capacity (LFDCC), Y^* can be depicted as follows:

$$Y^* = \frac{K_k}{1 + ae^{-bt} + \frac{a_k}{1 - b_k / b} e^{-b_k t}} \quad (4)$$

where $K = \frac{K_k}{1 + a_k e^{-b_k t}}$; K_k: ultimate carrying capacity; and a_k and b_k: coefficients.

$$\lambda \equiv \phi_1 - \phi_2 \left(ae^{-bt} + \frac{a_k}{1 - b_k / b} e^{-b_k t} \right) \quad (5)$$

where $\phi_1 = \frac{\eta}{b'}(1 + \phi)$ and $\phi_2 = \frac{\eta}{b'}\phi$: coefficients.

Learning coefficient λ can be depicted by the following general equation:

$$\lambda = \alpha - \beta e^{-\gamma t} \quad (6)$$

where $\alpha, \beta,$ and γ are positive coefficients.

The coefficient γ is a function depicted by the following function:

$$\gamma = \gamma\left((a,b), \left(\frac{a_k}{1 - b_k / b}, b_k \right) \right) \quad (7)$$

The second term in equation (7) is a function of factors governing dynamic carrying capacity and reflecting functionality of the innovative goods examined. Since this functionality decreases in long run, γ can be expressed by the following function:

$$\gamma = l - mt \quad (8)$$

Therefore, λ can be expressed by the following equation:

$$\lambda = \alpha - \beta e^{-(l - mt)t} \quad (9)$$

Equation (9) indicates convex with its peak at time $t = \frac{l}{2m}$ when $\frac{d\lambda}{dt} = 0$. Thus, a trajectory of λ starts from the initial level $\alpha - \beta$ (when $t = 0$), continues to increase its level by the period $t = \frac{l}{2m}$ with its peak level $\lambda_{max} = \alpha - \beta e^{-\frac{l^2}{4m}}$, and then changes to decreasing trend. At time $t = \frac{l}{m}$, its level decreases to the same level of initial period ($\alpha - \beta$), and continues to decrease to the lower level than initial period as demonstrated in **Fig. 1**.

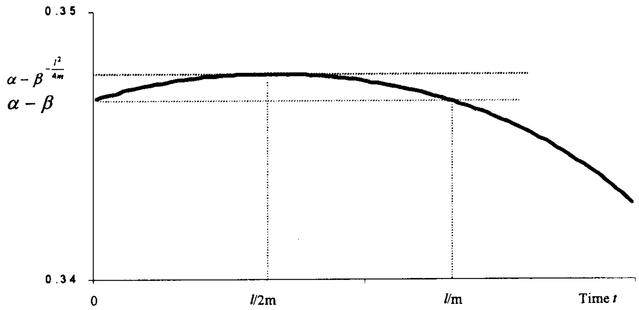
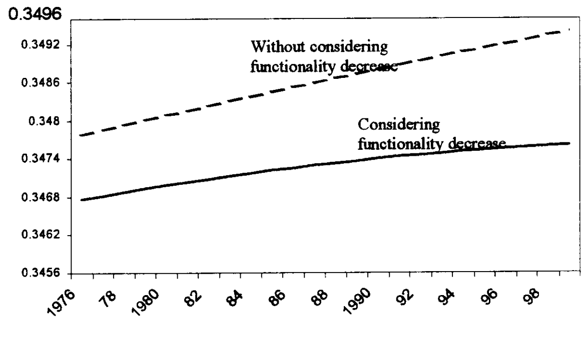


Fig. 1. Trajectory of Learning Coefficient.

On the basis of the foregoing analysis, the learning coefficient for Japanese PV development is estimated as follows:

$$\lambda = 0.3553 - 0.0086e^{-(0.0072 - .00011t)t} \quad (10)$$

Fig. 2 demonstrates the trends in learning coefficients measured by this learning coefficient function comparing with a trend estimated by a function without considering functionality decrease.



On the basis of these analyses and evaluations, learning coefficient function based on the general equation driven by an approximation of LFDCC and considering functionality decrease can be considered well reflecting the trend in learning coefficient of the development trajectory of innovative goods. Fig. 2 indicates that the trend measured without considering functionality decrease tends to demonstrate higher coefficient value than that of measured by considering functionality decrease.

Based on the foregoing assessment with respect to broad applicability of the learning coefficient function, Fig. 3 estimates the future trajectory of learning development in long run until 2050.

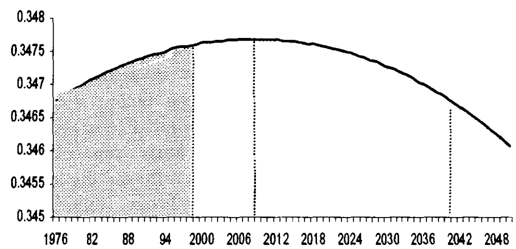


Fig. 3. Estimate of the Future Trajectory of Learning Coefficient in Japan's PV Development.

3. Learning and Diffusion of Technology

The analysis in Section 2 demonstrates the broad applicability of the learning coefficient function driven by LFDCC and considering functionality decrease.

Stimulated by these findings, this Section attempts to link learning and diffusion of technology.

3.1 Learning Coefficient Function Incorporating Functionality Decrease

Based on the analyses in Section 2, equation (5) can be depicted as follows by incorporating an additional term ($a_h e^{b_h t^2}$) reflecting functionality decrease in long run, and this should be equivalent to equation (9) over the time:

$$\lambda = \phi_1 - \phi_2 \left(ae^{-bt} + \frac{a_k}{1-b_k/b} e^{-b_k t} + a_h e^{b_h t^2} \right) \tag{5'}$$

$$= \alpha - \beta e^{-(l-mt)t} \tag{11}$$

where a_h: and b_h: coefficients reflecting functionality decrease.

Utilizing estimated LFDCC-LCFDE, trend in learning coefficient in Japan's PV development is illustrated in **Fig. 4** by comparing the trend in learning coefficient measured by the learning coefficient function considering functionality decrease as illustrated in Fig. 2 (general learning coefficient).

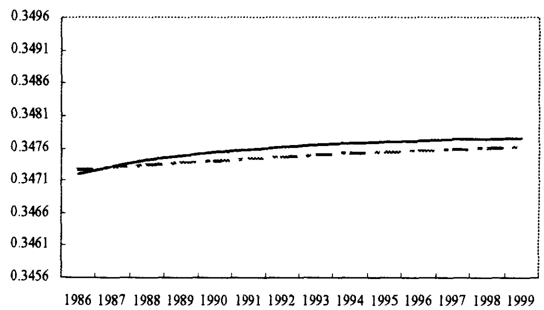


Fig. 4. Trends in Learning Coefficient in Japan's PV Development

3.2 Technology Diffusion Trajectory Reflecting Functionality Decrease Effects

The series of the analyses in 3.1 demonstrate that functionality decrease effects on learning coefficient inevitably affect the trajectory of technology diffusion in long run which compels a modification in the logistic growth function within a dynamic carrying capacity (LFDCC) depicted by equation (4). Furthermore, mathematical development process suggest that LFDCC could reflect functionality decrease effects in long run by adding an additional term ($a_h e^{b_h t^2}$), which was demonstrated as reflecting functionality decrease in long run, in its denominator as follows:

$$Y^*(t) = \frac{K_k}{1 + ae^{-bt} + \frac{a_k}{1-b_k/b} e^{-b_k t} + a_h e^{b_h t^2}} \tag{12}$$

Equation (12) suggests that diffusion trajectory would be depressed in long run by the functionality decrease term. Given the LFDCC incorporating functionality decrease effects (LFDCC-FDE) as enumerated by equation (12), its dynamic carrying capacity is enumerated as follows (see Appendix for mathematical development):

$$K(t) = \frac{K_k}{1 + a_k e^{-b_k t} + [b(b + 2b_h t)]a_h e^{b_k t^2}} \quad (13)$$

Equation (13) suggests that the impacts of the additional term derived from functionality decrease effects reveal significantly in depressing carrying capacity as time runs by in long run.

4. Institutional Dynamism Leading to a Dynamic Interaction between Learning, Diffusion and Spillover of Technology

The analysis in Section 3 demonstrates the significance of the interaction between learning and diffusion of technology. This interaction induces vigorous R&D activities which lead to increasing technology stock. Technology stock, in turn, as a direct result of R&D investment inevitably stimulates multi-factor learning. Multi-factor learning induces further increase in technology stock. This necessitates both indigenous R&D investment and effective utilization of spillover technology.

Trans-generational technology spillovers accumulates learning, and learning can be considered as one of the sources of spillovers as well as being considered as an effect of spillovers at the same time. Learning and spillovers together with technology stock generated by indigenous R&D enhance total factor productivity, as illustrated in **Fig. 5**, which in turn contributes to production increase. Increased production results in higher cumulative production which stimulates learning. Furthermore, it induces R&D investment, which in turn generates technology stock. Thus, an organic comprehensive structure led by institutional dynamism generating dynamic interaction between learning, diffusion and spillover of technology is constructed.

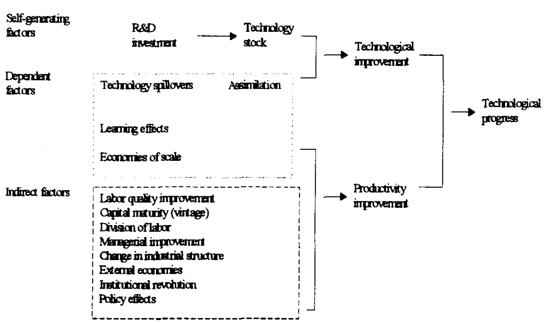


Fig. 5. Composition of Total Factor Productivity.

5. Conclusion

In light of the increasing significance of the systems approach in maximizing the effects of innovation by means of the effective utilization of the potential resources of innovation, this paper undertook theoretical analysis of this subject focusing on a dynamism between learning and diffusion of technology. An empirical demonstration was also attempted taking Japan's PV development trajectory, which follows the similar trajectory of IT's functionality development, over the last quarter century.

Noteworthy findings include:

(i) It was anticipated that the behavior of learning coefficient has close relevance with that of a logistic growth function within a dynamic carrying capacity. This coefficient was anticipated to increase as a consequence of cumulative learning effects and change to decreasing trend in long run as functionality decreases.

(ii) Such a dynamic convex behavior of learning coefficient was enumerated by an equation derived from a logistic growth function within a dynamic carrying capacity with an additional term reflecting functionality decrease in long run. It was demonstrated that this equation reflected the learning coefficient of Japan's PV firms, thereby the significance of this equation was demonstrated. This dynamic coefficient function incorporating functionality decrease effects revealed that an estimate without considering functionality decrease effects leads to higher estimate than that of estimated by reflecting functionality decrease effects.

(iii) Synchronizing this equation in a logistic growth function within a dynamic carrying capacity, an equation depicting diffusion trajectory of innovative goods incorporating functionality decrease effects was developed which demonstrates similar trajectory as actual one, thereby significance of this equation was demonstrated. A trajectory estimated by this equation demonstrates slightly lower diffusion trajectory than the trajectory estimated by a normal logistic growth function within a dynamic carrying capacity without considering functionality decrease effects.

References

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