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Impacts of functionality development on dynamism between learning and diffusion of technology

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Abstract

Under a long-lasting economic stagnation, a significant increase in R&D investment has become difficult. A practical solution could be found in a 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 the self-propagating nature of IT-driven innovation.

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

The effects of functionality decrease on learning coefficient and the consequent impacts on technology diffusion and its dynamic carrying capacity are analyzed. Fear of a vicious cycle between functionality decrease, deterioration of learning, stagnation of technology diffusion and its carrying capacity in the long run is demonstrated. Thereby, the significance of institutional dynamism leading to a dynamic interaction between learning, diffusion, and spillover of technology is identified.

Keywords: Technological learning; Dynamic learning coefficient; Diffusion of technology; Functionality development, Technology spillovers; Institutional dynamism

1. Introduction

While technological innovation has a significant contribution to socio-economic development, under long-lasting economic stagnation, the stagnation of technology development has become a crucial structural problem common to all advanced countries (OECD, 1998). Similarly, Japan has been suffering from a collapse of its long-lasting virtuous cycle between technology development and economic growth (Watanabe, 1995) leading to a vicious cycle between economic stagnation and the stagnation of R&D investment. Under such circumstances, a significant increase in R&D investment has become difficult, increasing the significance of the systems approach maximizing the effects of innovation as a system (Watanabe, 1997). 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 the self-propagating nature of IT-driven innovation (Watanabe et al., 2002a).

Prompted by these understandings, this article attempts to analyze the interacting dynamism of innovation in a comprehensive and organic system. As postulated by Ruttan (2001), innovation should be recognized as a very subtle entity subject to conditions of institutional systems. Therefore, theoretical analysis and empirical demonstration are attempted, focusing on the dynamism between learning and diffusion of technology taking place in Japan's PV development over the last quarter century. The PV development trajectory is taken as it follows a similar trajectory to IT's functionality development (Watanabe et al., 2001).

In line with the foregoing economic as well as technology stagnation, it is generally anticipated that func-

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tionality development in Japan's high-technology industry has decreased. The new functionality development created by electrical machinery, which shares one third of Japan's whole R&D expenditure, was dramatically exhausted in the 1990s (Watanabe et al., 2002b).

Such a decrease in the functionality development inevitably results in a decrease in learning effects (Price, 1965). As Cohen and Levinthal (1990) postulated, learning is cumulative and cumulative learning stimulates assimilation of spillover knowledge, which inevitably induces distribution of technology. Furthermore, as Watanabe et al. (2002b) demonstrated, the functionality development concept can be materialized by correlating technology elasticity to sales as well as logistic growth within a dynamic carrying capacity which depicts the diffusion of technology and its dynamic carrying capacity that represents the state of the functionality development (Watanabe et al., 2002b). Thus, a decrease in functionality development is anticipated to lead to a vicious cycle between a decrease in learning effects (which can be measured by a decrease in the learning coefficient), stagnation of technology diffusion and its dynamic carrying capacity (which represents a further decrease in functionality).

Following Arrow's pioneer postulate on " learning-by-doing" (Arrow, 1962), while a number of works analyzed the mechanism of learning and its effects (e.g., Rosenberg, 1976, and Cohen and Levinthal, 1990), none has analyzed dynamic hysteresis of the learning coefficient. Similarly, since Rogers' pioneering work on the diffusion of innovations (Rogers, 1962), a number of works have analyzed the diffusion process of technology (e.g., Metcalfe, 1970, 1981), as well as governing factors of the diffusion trajectory (e.g., Meyer, 1994; Meyer and Ausbel, 1999), but none has linked the dynamic behavior of the learning coefficient with the trajectory of technology diffusion and its dynamic carrying capacity in a virtuous or vicious cycle perspective.

In light of the foregoing, this article, by means of theoretical analysis and empirical demonstration, attempts to analyze the effects of functionality decrease on the learning coefficient, and the consequent impacts on technology diffusion and dynamic carrying capacity are analyzed. Fear of a vicious cycle between functionality decrease, deterioration of learning, stagnation of technology diffusion and carrying capacity in the long run is demonstrated.

Section 2 attempts to analyze the dynamic behavior of the 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 leading to a dynamic construction between learning, diffusion, and spillovers of technology. Section 5 briefly summarizes the findings obtained from the analyses and extracts policy implications for effective utilization of potential resources of innovation.

2. Dynamic behavior of learning coefficient

The learning exercise is a result of cumulative efforts and it is a long-range strategic concept rather than a short-term tactical concept. It represents the combined effects of a large number of factors and cumulative efforts.

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 (IEA, 2000) 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)[1]; andλ ($>$ 0): learning coefficient.

Taking the logarithm of eq. (1):

$$\ln P = \ln B - \lambda \ln Y^*. \tag{2}$$

Differentiating both sides of eq. (2) with respect to time t,:$\frac{d}{dt}\ln P = -\frac{d\lambda}{dt}\ln Y^* - \lambda\frac{d}{dt}\ln Y^*$ Since $\frac{d\lambda}{dt}$ is small enough[2], λ can be approximated as follows:

$$-\lambda \approx \frac{\frac{d}{dt}\ln P}{\frac{d}{dt}\ln Y^*}. \tag{3}$$

In the case of innovative goods, prices can be depicted by a function of time t as demonstrated by the decreasing trend in PV prices in Japan, which is clearly illustrated in Fig. 1.

$$P = B'e^{-\eta t} \tag{4}$$

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

Fig. 1 demonstrates the statistically significant correlation between time t and prices P.From eq. (4) coefficient η can be obtained by the following equation:

[1] Given the production at time t, Y_t, cumulative production at time t, Y_t^*, can be measured as follows:$Y_t^* = Y_{t-l_t} + (1-\rho)Y_{t-1}^*$where l_t: lead time between production and operation; and ρ: depreciation rate.

[2] Fig. 4 demonstrates that $0.3467 \leq \lambda \leq 0.3477$,and, therefore, $\frac{d\lambda}{dt} \leq 0.003{\cdot}\lambda$.

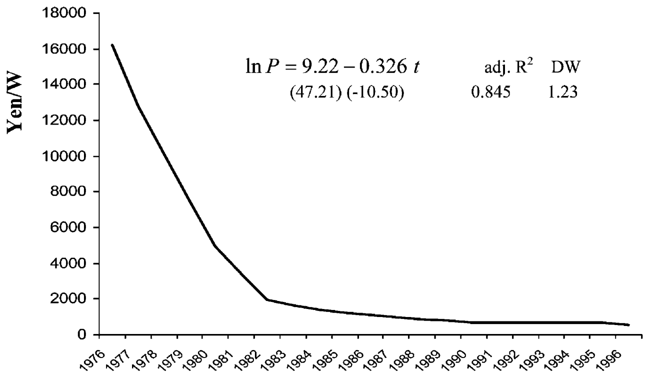

Fig. 1. Trend in PV prices in Japan (1976–1996) — Yen/W at 1985 fixed prices.

$$\frac{d\ln P}{dt} = -\eta. \tag{5}$$

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

$$\frac{dY^*}{dt} = bY^*(1-\frac{Y^*}{K}) \tag{6}$$

where b: coefficient; and K: carrying capacity.

Eq. (6) can be developed to

$$\frac{d\ln Y^*}{dt} = b(1-\frac{Y^*}{K}). \tag{7}$$

Provided that the 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 (see mathematical development in the Appendix):

$$Y^* = \frac{K_k}{1 + ae^{-bt} + \frac{a_k}{1-b_k/b}e^{-b_k t}} \tag{8}$$

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

Substituting Y^* in the right-hand side of eq. (7) for a trajectory depicted by eq. (8):

$$\frac{d\ln Y^*}{dt} \approx b\left(1-\frac{K_k/K}{1 + ae^{-bt} + \frac{a_k}{1-b_k/b}e^{-b_k t}}\right), \tag{9}$$

$$= b'\left(1-\frac{\phi}{1 + ae^{-bt} + \frac{a_k}{1-b_k/b}e^{-b_k t}}\right)$$

where b': adjusted coefficient, and ϕ ($<$ 1): adjustment coefficient.

Substituting the right-hand side of eqs. (5) and (9) for relevant factors of eq. (3) under certain conditions when $\phi\cdot\left(ae^{-bt} + \frac{a_k}{1-b_k/b}e^{-b_k t}\right) < < 1$, the learning coefficient λ can be approximated by the following equation:

$$\lambda = \frac{\eta}{b'}\left(\frac{1}{1-\frac{\phi}{1 + ae^{-bt} + \frac{a_k}{1-b_k/b}e^{-b_k t}}}\right)$$

$$\approx \frac{\eta}{b'}\left\{1 + \phi\left(1-\left(ae^{-bt} + \frac{a_k}{1-b_k/b}e^{-b_k t}\right)\right)\right\} \tag{10}$$

$$= \frac{\eta}{b'}\left\{(1 + \phi)-\phi\left(ae^{-bt} + \frac{a_k}{1-b_k/b}e^{-b_k t}\right)\right\}$$

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

where $\phi_1 = \frac{\eta}{b'}(1 + \phi)$ and $\phi_2 = \frac{\eta}{b'}\phi$: coefficients ($>$ 0).

Therefore, the learning coefficient λ can be depicted by the following general equation:

$$\lambda = \alpha-\beta\, e^{-\gamma t} \tag{11}$$

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

Eq. (10) suggests that a coefficient γ is a function depicted by the following function:

$$\gamma = \gamma\left((a, b),\ \left(\frac{a_k}{1-b_k/b},\ b_k\right)\right). \tag{12}$$

The second term in eq. (12) is a function of factors governing the dynamic carrying capacity and reflecting the functionality of the innovative goods examined (Watanabe et al., 2002b). Since this functionality decreases in the long run (Price, 1965), γ can be expressed by the following function:

$$\gamma = l-mt \tag{13}$$

where coefficients l and m are positive values.

Therefore, λ can be expressed by the following equation:

$$\lambda = \alpha-\beta\, e^{-(l-mt)t}. \tag{14}$$

Eq. (14) indicates a convex trend 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

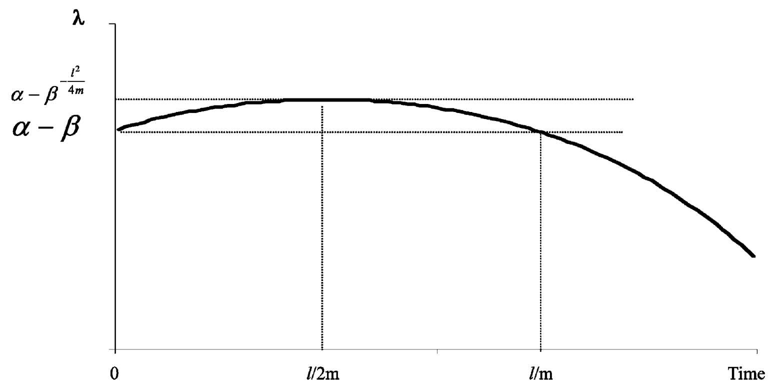

Fig. 2. Trajectory of learning coefficient.

Table 1
Comparison of learning coefficient functions for Japan's PV development (1976–1999)

Without considering functionality decrease		
$\ln P = 8.3000-(0.3565-0.0088\,e^{-0.0089\,t})\ln Y^{*}$	Adj. R^2	**DW**
(239.06) (45.91) (4.04) (2.45)	**0.990**	**0.81**
$\lambda = 0.3565-0.0088\,e^{-8.9120\,t}$		
Considering functionality decrease		
$\ln P = 8.2927-(0.3553-0.0086\,e^{-(0.0072-0.00011\,t)t})\ln Y^{*}$	adj. R^2	**DW**
(290.86) (50.36) (4.17) (3.22) (5.79)	**0.993**	**1.31**
$\lambda = 0.3553-0.0086\quad e^{-(0.0072-0.00011\ t)t}$		

level $\lambda_{\max} = \alpha-\beta\, e^{-\frac{l^2}{4m}}$, and then changes to a decreasing trend. At time $t = \frac{l}{m}$, its level decreases to the same level of the initial period $(\alpha-\beta)$, and continues to decrease to a lower level than the initial period as demonstrated in Fig. 2.

In order to demonstrate the significance of the foregoing general equation of the learning coefficient with respect to broader applicability — given that this significance is demonstrated —, and also to identify the behavior of this coefficient, an empirical analysis is conducted by taking Japan's PV development trajectory over the period 1976–1999. The results are summarized in Table 1 and Figs. 3 and 4.

Table 1 summarizes the comparison of learning coefficients without considering functionality decrease and

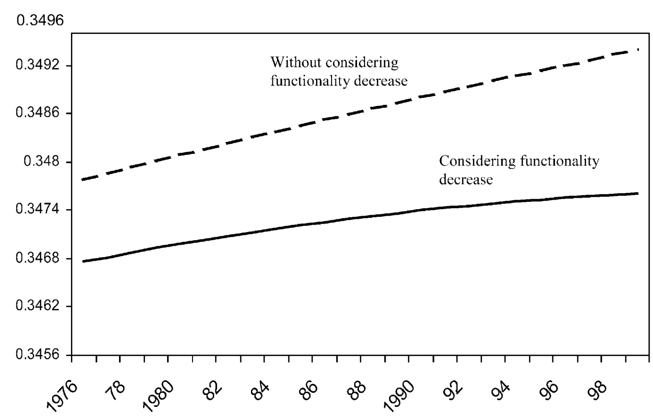

Fig. 3. Trends in learning coefficients in Japan's PV development (1976–1999).

Table 2
Learning coefficients of PV development in leading Japanese PV firms (1980–1990): Aggregate average of eight leading firms

Model: $P = A\cdot Y^{*\,-\lambda}\ \lambda = 0.347$		
$\ln P = 3.609-0.347\ln Y^{*}$	adj.R^2	DW
(73.40) (-22.80)	0.981	1.42

where P: solar cell production price (fixed price); and Y^{*}: cumulative solar cell production. The eight firms are: Sanyo Electric Co. Ltd., Kyocera Corp., Sharp Corp., Kaneka Corp., Fuji Electric Co. Ltd., and Hitachi Ltd. Source: C. Watanabe et al., 2001.

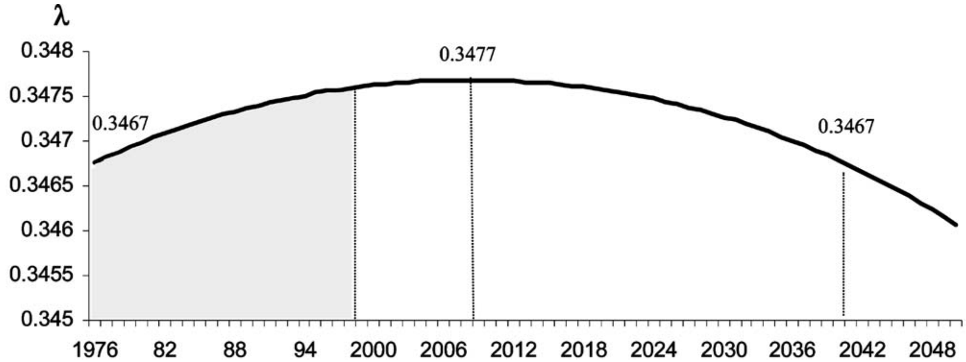

Fig. 4. Estimate of the future trajectory of learning coefficient in Japan's PV development (1976–2050).

by considering functionality decrease for Japan's PV development trajectory over the period 1976–1999.

Looking at Table 1 we note that the learning coefficient function considering the functionality decrease is statistically more significant than that without considering the functionality decrease. This result demonstrates that the effects of functionality decrease can not be overlooked in the long run.

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

$$\lambda = 0.3553-0.0086\ e^{-(0.0072-.00011\ t)t}. \qquad (15)$$

Fig. 3 demonstrates the trends in learning coefficients measured by this learning coefficient function by comparing with a trend estimated by a function without considering functionality decrease.

Looking at Fig. 3 we note that the learning coefficient of Japan's PV development over the last quarter century is approximately 0.347, sustaining a slight increasing trend corresponding to the learning coefficient of Japan's leading PV firms as demonstrated in Table 2.

On the basis of these analyses and evaluations, the learning coefficient function based on the general equation driven by an approximation of LFDCC and considering the functionality decrease can be considered to reflect well the trend in the learning coefficient of the development trajectory of innovative goods. Fig. 3 indicates that the trend measured without considering functionality decrease tends to demonstrate a higher coefficient value than that measured by considering functionality decrease.

Based on the foregoing assessment with respect to the broad applicability of the learning coefficient function, Fig. 4 estimates the future trajectory of learning development in the long run until 2050.

Looking at Fig. 4 we note that the learning coefficient demonstrates a convex trend with its peak at 0.3477 in 2009 (at time $t = \dfrac{l}{2m}$ when $\dfrac{d\lambda}{dt} = 0$). After that, it changes to a decreasing trend. In 2041 it reaches a level equal to its initial level (0.3467) and continues to decrease to a lower level than the initial level. This clearly demonstrates the significance of the trajectory of the learning coefficient considering the functionality decrease in the long run. The trend estimated in Fig. 3 demonstrates a partial section of the trend in the learning coefficient before it reaches its peak.

3. Learning and diffusion of technology

The analysis above 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 the last section, eq. (10) can be depicted as follows by incorporating an additional term ($a_h e^{b_h t^2}$) reflecting the functionality decrease in the long run[3]and this should be equivalent to eq. (14) over the time:

[3] This term is equivalent to –*mt* in eq. (13). Given the small value of the power of the exponent, the second term of equation (10') can be approximated as follows:

$$-\phi_2\left[a(1-bt) + \frac{a_k}{1-b_k/b}(1-b_k) + a_h(1 + b_h t^2)\right]$$

$$= -\left[\left(a + \frac{a_k}{1-b_k/b} + b_h\right)\phi_2 - \left(ab + \frac{a_k b_k}{1-b_k/b}\right)\phi_2 t + a_h b_h \phi_2 t^2\right] \quad \text{(A)}$$

$$\equiv -(\alpha_1-\beta_1\ t + \gamma_1\ t^2)$$

while the second term of eq. (14) can be approximated as follows:

$$-\beta[1-(l-mt)t] = -\beta(1-lt + mt^2) \equiv -(\alpha_2-\beta_2\ t + \gamma_2 t^2). \qquad \text{(B)}$$

Under the condition within a certain period, $\alpha_1 = \alpha_2$, $\beta_1 = \beta_2$ and $\gamma_1 = \gamma_2$, the structure of the additional term $a_h e^{b_h t^2}$ can satisfy the requirement of equations (A) and (B) are equivalent.

Table 3
Estimation results for the development trajectory of Japan's PV (1976–2000)

K_K	a	b	a_K	b_K	adj. R^2	DW
$9.453\text{x}10^3$ (3.31)	$1.796\text{x}10^4$ (1.57)	$5.870\text{x}10^{-1}$ (5.74)	$9.472\text{x}10^2$ (3.89)	$1.670\text{x}10^{-1}$ (29.79)	0.998	0.64

$$\lambda = \phi_1 - \phi_2\left(ae^{-bt} + \frac{a_k}{1-b_k/b}e^{-b_kt} + a_he^{b_ht^2}\right) \tag{10'}$$

$$= \alpha - \beta\, e^{-(l-mt)t} \tag{14}$$

(14)where a_h: and b_h: coefficients reflecting functionality decrease.

Comparing equations (10') and (14), the following conditions can be obtained within a certain period[4]:

$$\alpha = \phi_1 + \varepsilon_1, \tag{15}$$

$$\phi_2ae^{-bt} + \frac{\phi_2a_k}{1-b_k/b}e^{-b_kt} + \phi_2a_he^{b_ht^2} \tag{16}$$

$$= \beta\, e^{-(lt-mt^2)} + \varepsilon_2,$$

$$W(t) = \phi_2 \cdot J(t) + \phi_2 \cdot a_h\, e^{b_h\, t^2} \tag{17}$$

where

$$W(t) \equiv \beta e^{-(l-mt)t} \tag{18}$$

$$J(t) \equiv a\, e^{-bt} + \frac{a_k}{1-b_k/b}\, e^{-b_kt}. \tag{19}$$

Since α and $W(t)$ are identified by eq. (15), and $J(t)$ can be identified by LFDCC enumerated by eq. (8), ϕ_1 as well as ϕ_2, a_h, and b_h can be identified by eqs. (15) and (17), respectively. Following these steps and applying the data obtained from empirical analysis on Japan's PV development trajectory as well as the learning coefficient trajectory in the last section, the LFDCC driven learning coefficient function incorporating functionality decrease effects (LFDCC–LCFDE) as depicted in eq: (10') is identified.

Coefficients a, b, a_k and b_k as well as the ultimate carrying capacity K_k for Japan's PV development trajectory over the period 1976–2000 are estimated in Table 3.

Coefficients ϕ_1, ϕ_2, a_h and b_h governing LFDCC–LCFDE for Japan's PV development are also estimated by the following approach.

First, by means of a preparatory regression using Shazam over the period 1976–2000 aiming at identifying asymptotes of the additional term ($a_he^{b_h\, t^2}$) reflecting the functionality decrease in long run, it was confirmed that

$$\frac{a_h}{J(t)} << 1, \tag{17(1)}$$

$$b_h\, t^2 << 1. \tag{17(2)}$$

From eq. (17), and taking the approximation based on eq: (17(1)) and eq: (17(2)):

$$\ln W(t) = \ln\phi_2[J(t) + a_he^{b_h\, t^2}] = \ln\phi_2 \cdot J(t)$$

$$\left[1 + \frac{a_h}{J(t)}\, e^{b_h\, t^2}\right] \approx \ln\phi_2 + \ln J(t) \tag{17(3)}$$

$$+ \frac{a_h}{J(t)}\, e^{b_h\, t^2} \approx \ln\phi_2 + \ln J(t) + \frac{a_h}{J(t)}(1 + b_h\, t^2)$$

$$= \ln\phi_2 + \left(\ln J(t) + \frac{a_h}{J(t)}\right) + a_h . b_h\, \frac{t^2}{J(t)}.$$

ln $J(t)$ can be approximated as follows[5]

$$\ln J(t) = \eta_1 - \eta_2\frac{1}{J(t)} \tag{17(4)}$$

where η_1 and η_2: coefficients.

Substituting $\frac{1}{J(t)}$ in eqs. (17) and (4)) for $\frac{1}{J(t)}$ in eqs. (17) and (3):

$$\ln W(t) = \left(\ln\phi_2 + a_h \cdot \frac{\eta_1}{\eta_2}\right) + \left(1 - \frac{a_h}{\eta_2}\right)\ln J(t) \tag{17(5)}$$

$$+ a_h \cdot b_h\frac{t^2}{J(t)}$$

$$\equiv \omega_1 + \omega_2\ln J(t) + \omega_3 \cdot \frac{t^2}{J(t)} \tag{17(6)}$$

where

$$\omega_1 = \ln\phi_2 + a_h \cdot \frac{\eta_1}{\eta_2} \tag{17(7)}$$

$$\omega_2 = 1 - \frac{a_h}{\eta_2} \tag{17(8)}$$

$$\omega_3 = a_h \cdot b_h. \tag{17(9)}$$

[4] These conditions can be satisfied and the requirements can be met after a certain period.

[5] Eq. (11) suggests that under certain conditions, J (t) can be approximated as follows: $J(t) \approx \beta e^{\gamma t}(0<\beta, 0<\gamma \ll 1)\ln J(t) = \ln\beta - \gamma\, t = (\ln\beta + 1) - (1 + \gamma t) \approx (1 + \ln\beta) - e^{\gamma t} = (1 + \ln\beta) - \frac{\beta}{J(t)} \equiv \eta_1 - \eta_2\frac{1}{J(t)}$.

From eqs. (17) and (8):

$$a_h = (1-\omega_2)\,\eta_2. \qquad (17(10))$$

From eqs. (17) and (9):

$$b_h = \frac{\omega_3}{a_h} = \frac{\omega}{(1-\omega_2)\,\eta_2}. \qquad (17(11))$$

From eqs. (17) and (7):

$$\ln\phi_2 = \omega_1 - a_h\cdot\frac{\eta_1}{\eta_2} = \omega_1-(1-\omega_2)\,\eta_1\phi_2 \qquad (17(12))$$

$$= Exp\,(\omega_1-(1-\omega_2)\,\eta_1).$$

By means of regression analyses over the period 1981–2000 utilizing data obtained from Tables 1 and 3, the following results were obtained:

$$\ln W(t) = -4.938 + 2.095\times10^{-2}\ln J(t) + 2.190\times10^{-4}\frac{t^2}{J(t)} - 2.811\times10^{-3}D \quad \text{adj.R}^2 \quad \text{DW} \qquad (17(13))$$

(− 2570.72) (60.45) (3.86)

(− 3.93) 0.998 1.59

where D: dummy variables (1981, 1982, 1995 = 1, other years = 0).

$$\ln J(t) = 8.360-1.177\frac{1}{J(t)} \quad \text{adj.R}^2 \ DW\ (18.52) \qquad (17(14))$$

(− 12.26) 0.931 1.33

(by means of the Cochrun–Orcutt treatment).

From eqs. (17),(13)) and 17(14)), coefficients a_h, b_h, and ϕ_2 were identified as follows:$a_h = (1-2.095\times10^{-2})\times1.177 = 1.152$$b_h = 2.190\times10^{-4}/\ 1.152 = 1.901\times10^{-4}$$\phi_2 = Exp\,(-4.938-(1-2.095\times10^{-2})\times8.360) = Exp\,(-13.122) = 2.001\times10^{-6}$.

By applying the identified a_h, b_h, and ϕ_2 to eq: (10’) and taking balance with eq. (14), ϕ_1 ($= \alpha + \epsilon_1$) was estimated as:$\phi_1 = 3.478\times10^{-1}$.

Therefore, LFDCC–LCFDE is enumerated as follows:

$$\lambda = 3.478\times10^{-1} - 2.001\times10^{-6}(1.796\ \times10^4e^{-5.870\times10^{-1}\ t} + 1.324\times10^3e^{-1.67\times10^{-1}\ t} + 1.152\ e^{1.901\ \times10^{-4}\ t^2}) \qquad (20)$$

Utilizing the estimated LFDCC–LCFDE, thr trend in the learning coefficient in Japan’s PV development is illustrated in Fig. 5 by comparing the trend in learning coefficient measured by the learning coefficient function considering the functionality decrease as illustrated in Fig. 3 (general learning coefficient). The estimate by LFDCC–LCFDE also corresponds to the learning coefficient of Japan’s leading PV firms as demonstrated in Table 2. Fig. 5 shows that the estimate by LFDCC–LCFDE demonstrates a convex behavior of the learning coefficient more clearly.

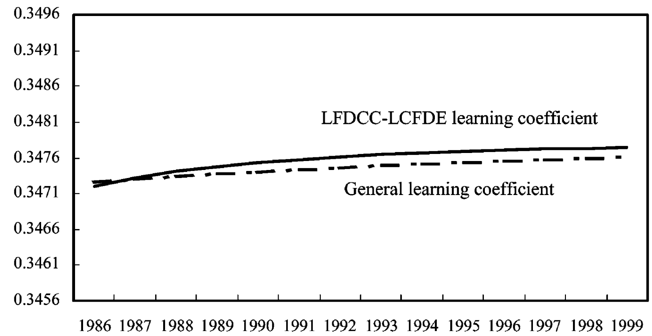

Fig. 5. Trends in learning coefficient in Japan’s PV development (1986–1999).

Table 4 compares the learning coefficients measured by both approaches, demonstrating that the learning coefficient estimated by LFDCC–LCFDE is statistically slightly more significant that that of the estimate by the general learning coefficient approach.

These analyses demonstrate the reliability of (i) the learning coefficient function considering functionality decrease effects (eq. (14) and (10’), and (ii) the mathematical structure of the factor reflecting functionality decrease in long run ($a_h\ e^{b_h\ t^2}$in eq: (10’). In addition, Table 4 demonstrates that LFDCC–LCFDE depicts better behavior than that of the general coefficient function.

3.2. Technology diffusion trajectory reflecting functionality decrease effects

The series of the analyses the previous section demonstrates that functionality decrease effects on the learning coefficient inevitably affect the trajectory of technology diffusion in the long run, compelling a modification in the logistic growth function within a dynamic carrying capacity (LFDCC) depicted by eq. (8). Furthermore, a mathematical development process from eq. (6) to eq. (10) together with eq: (10’) suggests that LFDCC could reflect functionality decrease effects in the long run by adding an additional term ($a_he^{b_h\ t^2}$), which was demonstrated as reflecting functionality decrease in the long run, in its denominator as follows:

$$Y^*(t) = \frac{K_k}{1 + ae^{-bt} + \dfrac{a_k}{1-b_k/b}e^{-b_kt} + a_he^{b_ht^2}}. \qquad (21)$$

Eq. (21) suggests that the diffusion trajectory would be depressed in the long run by the functionality decrease term. Given the LFDCC incorporating functionality decrease effects (LFDCC–FDE) as enumerated

Table 4
Comparison of learning coefficient for Japan's PV development (1982–1999)

LFDCC–LCFDE			
$\ln P = 8.0588 - 0.8446\lambda(t)\ln Y*$ (226.49)(−38.27) General learning coefficient	adj.R^2 0.98865	DW 1.993	AIC –111.33
$\ln P = 8.0611 - 0.8462\lambda(t)\ln Y*$ (225.81)(−38.20)	adj.R^2 0.98861	DW 1.988	AIC –111.27

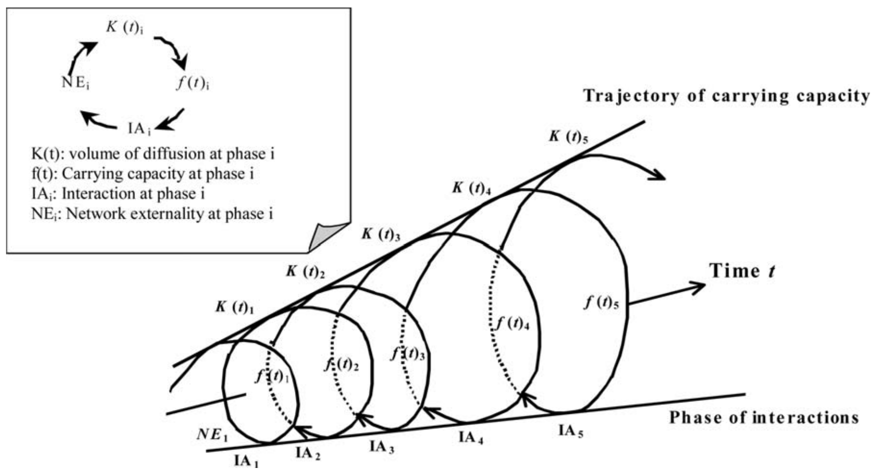

Fig. 6. Mechanism in creating a new carrying capacity in the process of IT diffusion. Original source: Watanabe et al., 2001.

by eq. (21), its dynamic carrying capacity is enumerated as follows (see Appendix for mathematical development):

$$K(t) = \frac{K_k}{1 + a_k e^{-b_k t} + [b(b + 2b_h\, t)]\, a_h\, e^{b_h t^2}}. \quad (22)$$

Eq. (22) suggests that the impacts of the additional term derived from functionality decrease effects are significantly revealedin the depressing carrying capacity over time.

Given the mechanism in creating a new carrying capacity in the process of IT diffusion as illustrated in Fig. 6[6], a decrease in carrying capacity reacts to a decrease in diffusion, which again decreases carrying capacity resulting in a a vicious cycle between stagnation of diffusion and carrying capacity as illustrated in Fig. 7. At the same time, a decrease in carrying capacity accelerates the obsolescence of technology.

Fig. 7 suggests that systems restructuring is indispensable for a virtuous cycle, and activation of interaction with institutional systems plays a significant role for this restructuring.

Fig. 8 and Table 5 demonstrate the trajectory of Japan's PV development measured by eq. (21) compar-

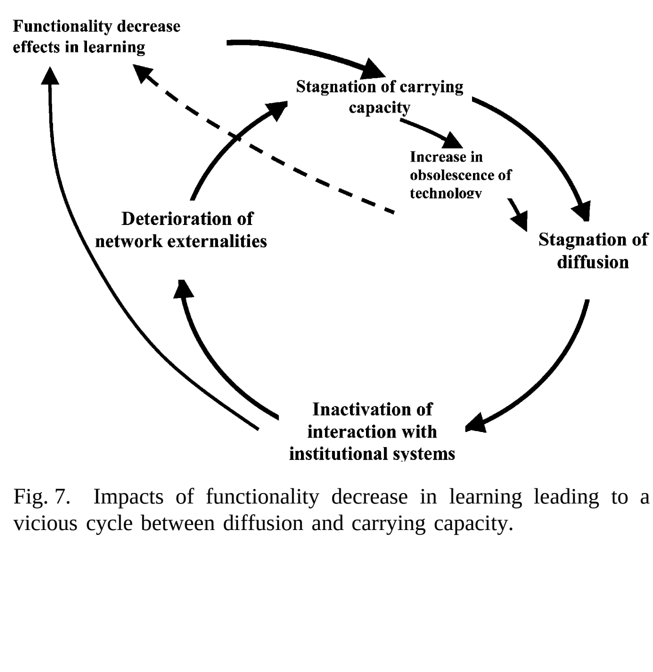

Fig. 7. Impacts of functionality decrease in learning leading to a vicious cycle between diffusion and carrying capacity.

[6] In the process of IT diffusion, the number of users increases as time passes, which induces interaction with institutions leading to increasing potential users by increased value and function as the network externalities gain momentum. Thus, IT creates new demand in this development process and new functionality is formed which in turn enhances user interaction. Thus, the interactive self-propagating behavior continues (Watanabe et al., 2002a).

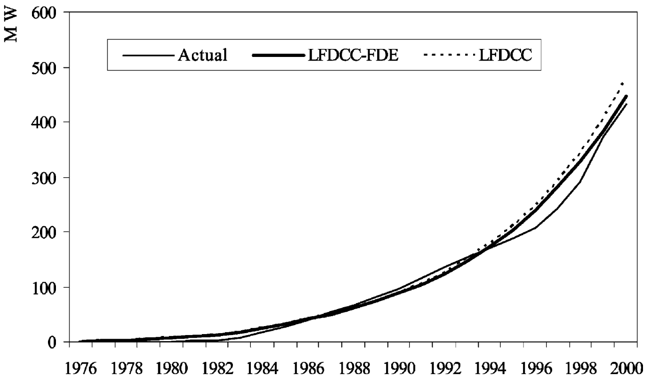

Fig. 8. Diffusion trajectory of Japan's PV development (1976–2000): MW.

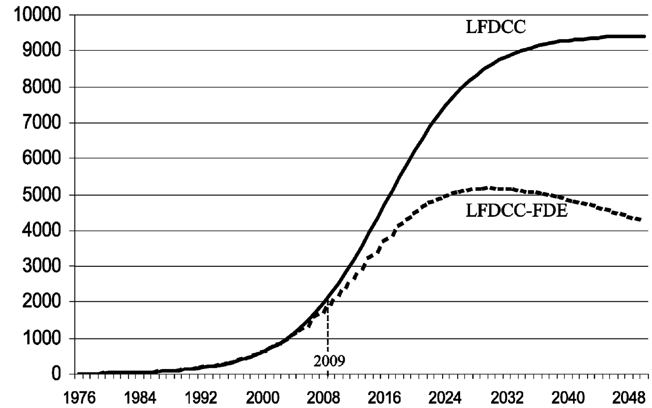

Fig. 9. Estimates of the trajectory of dynamic carrying capacity in Japan's PV development (1976–2050): MW.

Table 5
Comparison of diffusion trajectory estimates in Japan's PV development (1986–2000): MW

Year	Actual	LFDCC–FDE	LFDCC
1986	40.43	41.12	41.34
1987	53.63	50.52	50.86
1988	66.43	61.28	61.77
1989	80.63	73.66	74.38
1990	97.43	87.98	89.01
1991	117.23	104.62	106.10
1992	136.03	124.00	126.10
1993	152.73	146.60	149.56
1994	169.23	172.95	177.11
1995	186.63	203.65	209.48
1996	207.83	239.33	247.50
1997	242.83	280.71	292.12
1998	291.83	328.52	344.41
1999	371.83	383.55	405.60
2000	432.76	446.56	477.05

ing it with that estimated by LFDCC as well as the actual trend.

Fig. 8 and Table 5 demonstrate that the LFDCC–FDE estimate is slightly closer to the actual trend than that estimated by LFDCC as time passes. In addition, they demonstrate that as far as the estimate by 2000 is concerned, there are no substantial impacts with respect to the foregoing vicious cycle between stagnation of carrying capacity and diffusion derived from the functionality decrease effects in learning.

However, Fig. 9, which estimates the future trajectory of dynamic carrying capacity in the long run by using eq. (22), indicates that in the long run, the carrying capacity will be dramatically stagnated by functionality decrease effects, providing a significant threat of a vicious cycle as illustrated in Fig. 7. Fig. 9 indicates that this stagnation becomes distinct after the year 2009, corresponding to the year when the learning coefficient begins to decrease as estimated in Fig. 4.

All support the significance of incorporating functionality decrease effects in estimating both learning coefficients and diffusion trajectory of innovative goods. In addition, the foregoing analysis demonstrates the significance of the interaction between learning and diffusion of technology.

3.3. *Linking learning and diffusion of technology*

On the basis of the foregoing mathematical analysis and empirical demonstration, interaction between learning and diffusion of technology is identified, leading to systematic measurement of (i) LFDCC (logistic growth function within a dynamic carrying capacity)-based learning coefficient incorporating functionality decrease effects (LFDCC–LCFDE) and (ii) LFDCC incorporating functionality decrease effects (LFDCC–FDE) as illustrated in Fig. 10. Table 6 summarizes an algorithm for this stepwise systematic measurement.

4. Institutional dynamism leading to a dynamic interaction between learning, diffusion and spillover of technology

The analysis in the previous section 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 (**T**). Technology stock, in turn, as a direct result of R&D investment (**R**) inevitably stimulates multi-factor learning (**MFL**) (Cohen and Levinthal, 1989; Kouvaritakis et al., 2000). Multi-factor learning induces further increase in technology stock. This necessitates both indigenous R&D investment and effective utilization of spillover technology ($\mathbf{T_s}$).

Trans-generational technology spillovers accumulate learning, and learning can be considered as one of the sources of spillovers at the same time as being considered as an effect of spillovers. Learning and spillovers

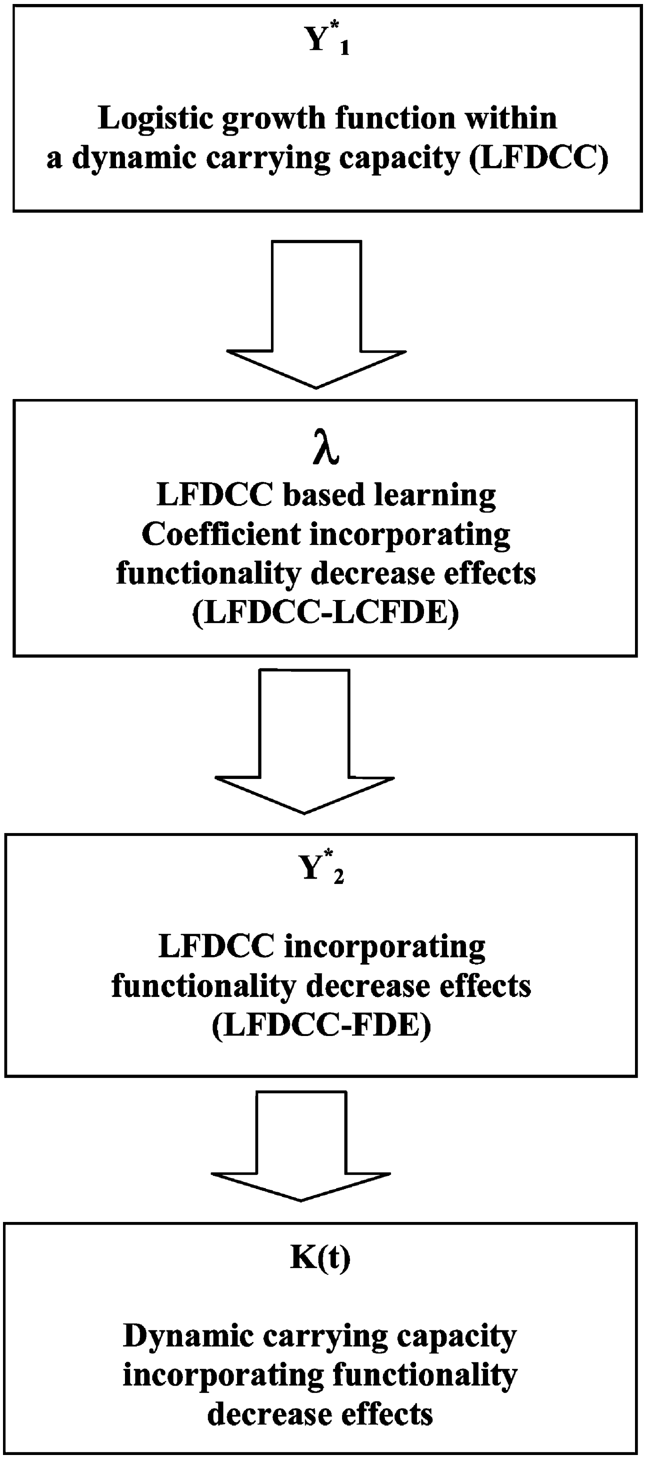

Fig. 10. Steps for measurement of LFDCC–LCFDE and LFDCC–FDE.

together with technology stock generated by indigenous R&D enhance total factor productivity (**TFP**), as illustrated in Fig. 11, which in turn contributes to production increase (**Y**). Increased production results in higher cumulative production (**Y**∗), 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.

A scheme in generating this dynamism is summarized in Table 7.

Fig. 12 illustrates an institutional dynamism leading to the foregoing dynamic interaction between learning, diffusion, and spillover of technology.

As analyzed in the previous section, systems restructuring is indispensable for shifting a vicious cycle between stagnation of diffusion and carrying capacity, and activation of interaction with institutional systems playing a significant role for this restructuring.

Fig. 12 supports these postulate and suggests the significance of institutional elasticity for activating interaction with institutional systems leading to a positive dynamic interaction between learning, diffusion, and spillovers of technology.

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 article undertook a 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 a similar trajectory to IT's functionality development, over the last quarter century.

Based on these analyses, dynamism between learning and diffusion of technology was elucidated, thereby the effects of functionality decrease on learning coefficient and consequent impacts on technology diffusion and its carrying capacity were identified.

Noteworthy findings include:

1. On the basis of intensive empirical analyses and reviews of proceeding works, it was anticipated that the behavior of the 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 a decreasing trend in the long run as functionality decreases.
2. Such a dynamic convex behavior of the 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 the long run. On the basis of an empirical analysis by applying this equation to Japan's PV development trajectory over the last quarter century, it was demonstrated that this equation reflected the learning coefficient of Japan's PV firms,

Table 6
The algorithm for systematic measurement of learning coefficient and diffusion trajectory based on a logistic growth function within a dynamic carrying capacity and incorporating functionality decrease effects (LFDCC–LCFDE and LFDCC–FDE)

1st step	Estimate a trajectory of Y∗ by means of a logistic growth function within a dynamic carrying capacity (LFDCC) approach $Y_1^* = \dfrac{K_k}{1 + ae^{-bt} + \dfrac{a_k}{1-b_k/b}e^{-b_k t}}$	(i)
2nd step	Estimate a general learning coefficient function considering functionality decrease effects $\lambda_1 = \alpha-\beta e^{(l-mt)t}(\lambda_{1\max} = \alpha-\beta e^{\frac{l^2}{4m}} \text{at} t = \dfrac{l}{2m}(\text{when}\dfrac{d\lambda}{dt} = 0))$	(ii)
3rd step	Estimate an adjusted LFDCC based learning coefficient λ by introducing a term reflecting functionality decrease effects $\lambda_2 = \phi_1-\phi_2\left(ae^{-bt} + \dfrac{a_k}{1-b_k/b}e^{-b_k t} + a_h e^{b_h t^2}\right)$	(iii)
4th step	Identify LFDCC based learning coefficient incorporating functionality decrease effects (LFDCC–LCFDE) $\lambda_3 = \alpha-\beta e^{-(l-mt)t} = \phi_1-\phi_2\left(ae^{-bt} + \dfrac{a_k}{1-b_k/b}e^{b_k t} + a_h e^{b_h t^2}\right)\Big(W(t) = \phi_2 \cdot J(t) +$ $\phi_2 \cdot a_h e^{b_h t} \text{where } W(t) \equiv \beta e^{-(l-mt)t} \text{ and } J(t) \equiv ae^{-bt} + \dfrac{a_k}{1-b_k/b}e^{-b_k t}\Big)$	(iv)
5th step	Identify LFDCC incorporating functionality decrease effects (LFDCC–FDE) $Y^* = \dfrac{K_k}{1 + ae^{-bt} + \dfrac{a_k}{1-b_k/b}e^{-b_k t} + a_h e^{b_h t^2}}$	(v)
6th step	Identify dynamic carrying capacity for LFDCC–FDE $K(t) = \dfrac{K_k}{1 + a_k e^{-b_k t} + [b(b + 2b_h t)]a_h e^{b_h t^2}}$	(vi)

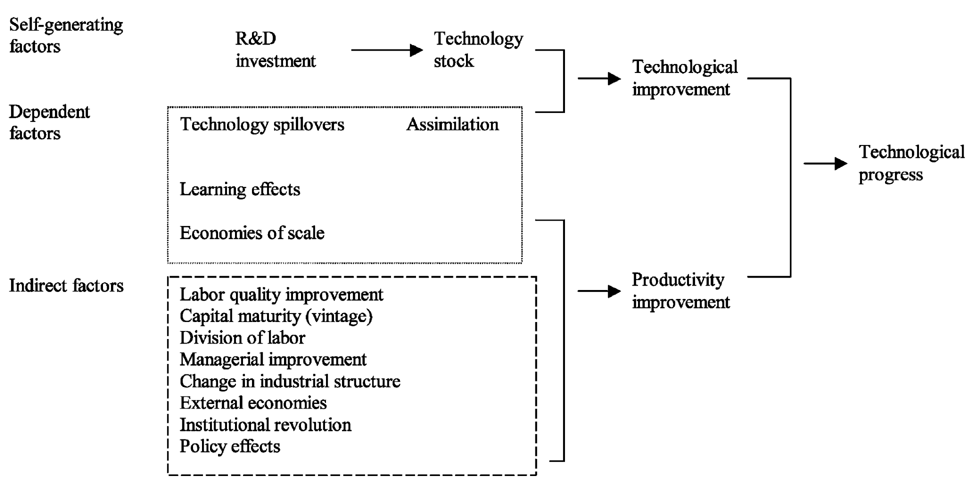

Fig. 11. Composition of total factor productivity (TFP).

thereby demonstrating the significance of this equation. This dynamic coefficient function incorporating functionality decrease effects revealed that an estimate without considering functionality decrease effects leads to a higher estimate than that estimated by reflecting functionality decrease effects.

3. 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 a similar trajectory to the actual one, thereby demonstrating the significance of this equation. A trajectory estimated by this equation demonstrates slightly lower diffusion trajectory

Table 7
Scheme in generating dynamism between learning, diffusion and spillover of technology

(i)	Technology stock as a direct result of R&D investment inevitably stimulates multifactor learning (MFL).
(ii)	MFL induces technological progress (TP).
(iii)	Technological progress (TP) necessitates both indigenous R&D (R) and resulting T_i and effective utilization of spillover technology (T_s).
(iv)	Trans-generational spillovers accumulates learning
(v)	Learning can be considered as one of the sources of spillovers as well as being considered as an effect of spillovers.
(vi)	Learning, spillovers together with technology stock generated by R&D enhance TFP.
(vii)	Enhanced TFP contributes to production increase (Y).
(viii)	Increased production leads to higher cumulative production (Y^*)which stimulates learning, in addition, it induces R&D investment which in turn generates technology stock.

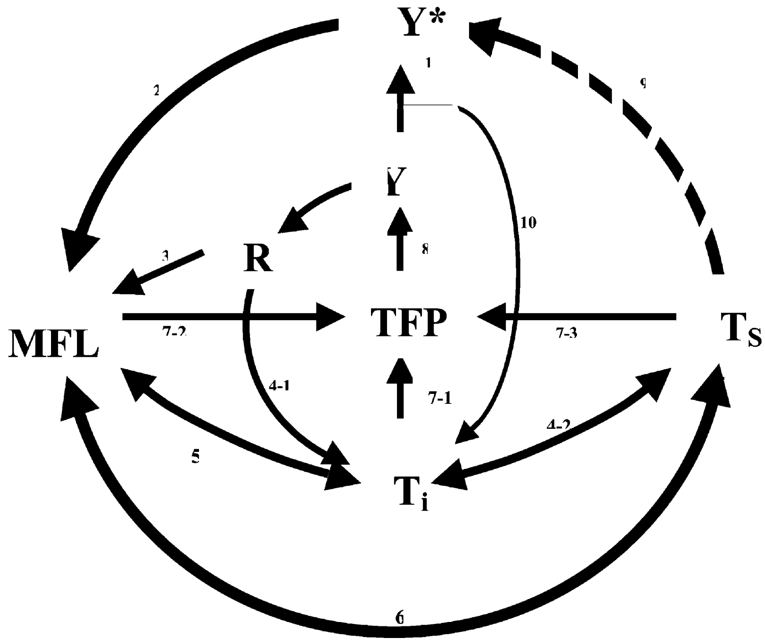

Fig. 12. Institutional dynamism leading to a dynamic interaction between learning, diffusion and spillover of technology.

than the trajectory estimated by a normal logistic growth function within a dynamic carrying capacity without considering functionality decrease effects. This was considered due to a “depression effect” as a consequence of functionality decrease.

4. Based on this new logistic growth function within a dynamic carrying capacity incorporating functionality decrease effects, the impacts of this functionality decrease on the dynamic carrying capacity was analyzed. The analysis identified that this impact is not so significant in the short term, but a significant impact in the long run in stagnating carrying capacity was revealed. In addition, it was identified that the decrease in this carrying capacity accelerates obsolescence of technology. This significant impact was identified to lead to a vicious cycle between stagnating carrying capacity and diffusion trajectory.

Important suggestions supportive to nations’ technology policy and firms’ R&D strategy in light of the maximum utilization of the potential resources for innovation under a long-lasting economic stagnation while facing a new paradigm initiated by an information society can be focused on the following points:

1. Systems restructuring is indispensable for shifting a vicious cycle between stagnation of diffusion and carrying capacity. Given the IT’s self-propagating nature formation process in which interaction with institutions plays a significant role, activation of interaction with institutional systems plays a significant role in this restructuring.
2. As a consequence, a way to lead a positive dynamic interaction between learning, diffusion, and spillovers of technology depends on institutional elasticity for activating interaction with institutional systems.

Given that the state of institutional systems constructs a virtuous cycle between techno-economic development of the nation, shifting the current vicious cycle to a virtuous cycle would be crucial.

Points of further works are summarized as follows:

1. Further elaboration of the relationship between the state of institutional system; more specifically, institutional elasticity, the state of innovation and diffusion, and the trend in functionality.
2. International comparison of the institutional elasticity and its effect on innovation and diffusion of technology.
3. Demonstration of the significance of institutional elasticity and its contribution to maximizing the effects of policy.

Appendix. Mathematical development of logistic growth function within a dynamic carrying capacity

Simple logistic growth function is expressed as follows:

$$\frac{df(t)}{dt} = bf(t)\left(1-\frac{f(t)}{K}\right) \quad \text{(A1 − 1)}$$

Given that innovation itself and the number of potential users change through the diffusion of innovation, logistic growth function within a dynamic carrying capacity is expressed by eq: (A1-2) where the number of potential users, carrying capacity (K) in the epidemic function is subject to a function of time t.

$$\frac{df(t)}{dt} = bf(t)\left(1-\frac{f(t)}{K(t)}\right). \quad \text{(A1 − 2)}$$

Eq: (A1-3) is obtained from eq: (A1-2):

$$\frac{df(t)}{dt} + (-b)f(t) = \left(-\frac{b}{K(t)}\right)\{f(t)\}^2. \quad \text{(A1 − 3)}$$

Eq: (A1-3) corresponds to the Bernoulli's differential equation expressed by eq: (A1-4):

$$\frac{dy}{dx} + V(x)y = W(x)y^n. \quad \text{(A1 − 4)}$$

Accordingly, eq: (A1-3) can be transformed to the linear differential equation expressed by eq: (A1-5).

$$\frac{dz(t)}{dx} + bz(t) = \frac{b}{K(t)} \text{ where } z(t) = \frac{1}{f(t)}. \quad \text{(A1 − 5)}$$

The solution for a linear differential equation (A1-6) can be obtained as (A1-7):

$$\frac{dy}{dt} + P(x)y = Q(x) \quad \text{(A1 − 6)}$$

$$y = \exp\left(-\int P(x)dx\right)\cdot\left\{\int \left(Q(x)\cdot\exp\left(\int P(x)dx\right)\right)dx + c\right\} \quad \text{(A1 − 7)}$$

Accordingly, the solution for eq: (A1-5) can be expressed as follows:

$$z(t) = \exp\left(-\int bdt\right)\cdot\left\{\int\left(\frac{b}{K(t)}\exp\left(\int bdt\right)\right)dt + c_1\right\} = \exp(-bt)\cdot\left\{b\int\left(\frac{1}{K(t)}\exp(bt)\right)dt + c_1\right\} \quad \text{(A1 − 8)}$$

$$\frac{1}{f(t)} = \exp(-bt)\cdot\left\{b\int\left(\frac{\exp(bt)}{K(t)}\right)dt + c_1\right\}. \quad \text{(A1 − 9)}$$

Assume that a carrying capacity $K(t)$increases sigmoidally, $K(t)$is expressed as follows:

$$K(t) = \frac{K_K}{1 + a_K\exp(-b_K t)} \quad \text{(A1 − 10)}$$

By substitution eq: (A1-10) for *K(t)* in eq: (A1-9), eq: (A1-11) is obtained:

$$\frac{1}{f(t)} = \left\{b\int\left(\frac{\exp(bt)}{K_K/(1 + a_K\exp(-b_K t))}\right) dt + c_1\right\}\exp(-bt) \quad \text{(A1 − 11)}$$

where

$$\int\left(\frac{\exp(bt)}{K_K/(1 + a_K\exp(-b_K t))}\right) dt = \frac{1}{K_K}\int\{\exp(bt) + a_K\exp((b-b_K)t)\}\, dt = \frac{1}{K_K}\left\{\int \exp(bt)dt + \int a_K\exp((b-b_K)t)\, dt\right\} = \frac{1}{K_K}\left\{\frac{1}{b}\exp(bt) + \frac{a_K}{b-b_K}\exp((b-b_K)t)\right\} + c_2. \quad \text{(A1 − 12)}$$

Accordingly, $f(t)$ can be developed as follows:

$$\frac{1}{f(t)} = b\left\{\frac{1}{K_K}\left\{\frac{1}{b}\exp(bt) + \frac{a_K}{b-b_K}\exp((b-b_K)t)\right\} + c_2 + c_1\right\}\cdot\exp(-bt)\frac{1}{f(t)} = \frac{1}{K_K}\left\{1 + \frac{b\cdot a_K}{b-b_K}\exp(-b_K t) + c_3\exp(-bt)\right\}\frac{1}{f(t)} \quad \text{(A1 − 13)}$$

$$= \frac{1}{K_K}\left\{1 + c_3\exp(-bt) + \frac{b\cdot a_K}{b-b_K}\exp(-b_K t)\right\}$$

$$f(t) = \frac{K_K}{1 + a\exp(-bt) + \frac{b\cdot a_K}{b-b_K}\exp(-b_K t)} \quad (A1-14)$$

Assuming that the carrying capacity $K(t)$ is expressed as follows:

$$K(t) = \frac{K_K}{1 + a_K e^{-b_K t} + a_h b(2b_h t + b)e^{b_h t^2}} \quad (A1-15)$$

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

From eq: (A1-9)

$$\frac{1}{f(t)} = \quad (A1-16)$$

$$\left\{b\int\left(\frac{e^{bt}}{K_K/(1 + a_K\, e^{-b_K t} + a_h b(2b_h t + b)\, e^{b_h t^2})}\right)dt + c_1\right\} e^{-bt}$$

where $\int\left(\frac{e^{bt}}{K_K/(1 + a_K\, e^{-b_K t} + a_h b\,(2b_h t + b)\, e^{b_h\, t^2})}\right)dt =$

$$\frac{1}{K_K}\int\{\, e^{bt} + a_K\, e^{(b-b_K)t} + a_h b\,(2b_h t + b)\, e^{b_h\, t^2 + b\, t}\}\, dt$$

$$= \frac{1}{K_K}\left\{\frac{1}{b}e^{bt} + \frac{a_K}{b-b_K}e^{(b-b_K)t} + a_h b e^{b_h t^2 + bt}\right\} + c_2.$$

Accordingly, $f(t)$ can be developed as follows:

$$\frac{1}{f(t)} = \left\{\frac{b}{K_K}\left\{\frac{1}{b}\, e^{bt} + \frac{a_K}{b-b_K}\, e^{(b-b_K)t} + a_h\, b\, e^{b_h t^2 + bt}\right\} + c_2 + c_1\right\} e^{-bt} \quad (A1-17)$$

$$f(t) = \frac{K_K}{1 + ae^{-bt} + \frac{ba_K}{b-b_K}e^{-b_K t} + a_h\, e^{b_h\, t^2}}. \quad (A1-18)$$

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