



Inside the learning dynamism inducing the resonance between innovation and high-demand consumption: A case of Japan's high-functional mobile phones

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ABSTRACT

Confronting the simultaneous global economic stagnation that has resulted in diminishing consumption, a new driver which can instill in customers an exciting story with their own initiative and thrills them with gratification of consumption is essential. Japan's mobile phone driven innovation may provide a constructive suggestion to this requirement.

On the basis of an empirical analysis focusing on the learning dynamism for innovative products in Japan's digital industry, this paper demonstrates the foregoing hypothetical anticipation. Based on measurement of dynamic learning coefficients for seven leading innovative products centered on mobile phones, the Granger causal test, Chow forecast test and wavelet analysis were conducted, and the significant role of mobile phones in leveraging broad dissemination, learning and absorption of core technologies essential to the advancement of digital industry was identified. Furthermore, significant role of demanding customers in inducing resonance between mobile phones learning and that of innovative products was demonstrated.

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1. Introduction

Contrary to the high technology miracle of the 1980s, Japan experienced long-lasting economic stagnation in the 1990s. This dramatic shift can be attributed to co-evolution between innovation and institutions in an industrial society and its disengagement in an information society [15]. However, a swell of new recovery emerged in the early 2000s [19]. Mobile phone driven innovation triggered a surge in co-evolution [16,19] as the number of mobile phone subscribers grew rapidly and exceeded those for fixed phones from 1998 as illustrated in Fig. 1. Furthermore, the introduction of i-mode service in February 1999 accelerated IP mobile diffusion which stimulated interaction with institutions [11]. Extensive interaction with institutions increased the learning coefficient [3] which enhanced functionality development from talk to see, see and talk, listen, take a picture, pay, and then watch [17]. Thus, self-propagating dynamism during the course of diffusion has been constructed as shown on the right side of Fig. 1 [2].

Such a high-functionality requirement is unique in Japan's institutions with abundant curiosity, assimilation proficiency, thoroughness in learning and absorption [16,19]. This can be satisfied by a tight operator–vendor relationship that leads to co-evolution between them [3,21]. This co-evolution is similar to the closed system of Japan's automobile manufacturers and their parts suppliers as well as printer and personal computer companies [18] in that it involves leading electrical machinery firms engaging in severe competition to satisfy institutional technology spillover requirements raised by demanding customers in a self-propagating way [17]. Thus, dual co-evolution through (i) market learning and (ii) operator–vendor interaction has been

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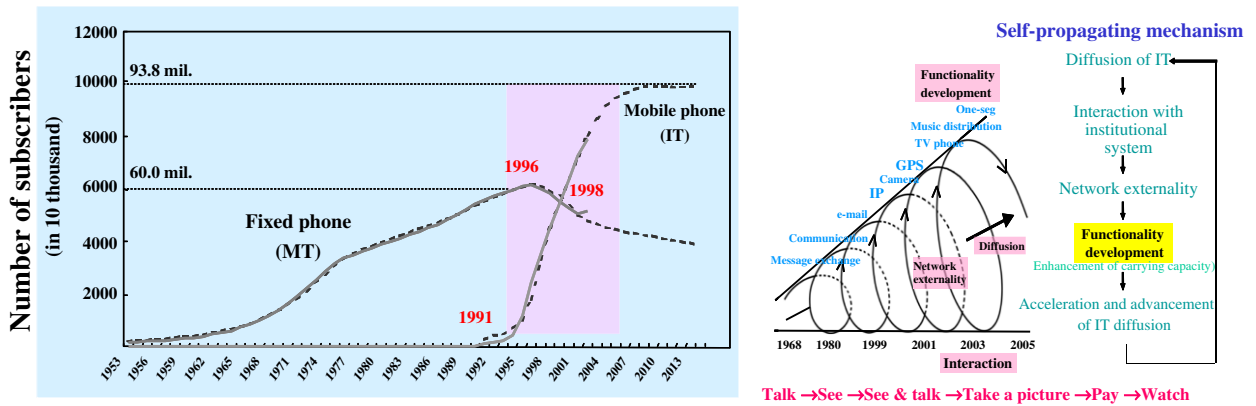


Fig. 1. Diffusion trajectories for fixed and mobile phones in Japan.

constructed in Japan's mobile phone development as illustrated in Fig. 2 [3,20]. This dual co-evolution induced the mobile phone driven innovation that emerged at the beginning of the 2000s and stimulated reactivation of Japan's economy [16,19]. Japan's leading Information and Communication Technology (ICT) think tank firm ICR [9] demonstrated that while the share of Japan's ICT industry in its GDP remained 2.2% in 1995 and 2/3 of that of automobile industry (AI: 3.3%), it increased to 3.5% in 2000 exceeding the share of AI (3.2%) and 4.3% in 2004 while that of AI was 3.5%. ICR stressed that significant driver leading ICT industry's conspicuous jump can be attributed to dramatic increase in mobile industry sharing 20.8% and 30.7% in IT in 2000 and 2004, respectively.

Mobile phone driven innovation can be attributed to both indigenous strength in manufacturing technology and the effects of cumulative learning from digital technology [11]. Watanabe et al. [17] demonstrated that effective utilization of learning effects can be the sources of its self-propagating development. It acquired new functionality from digital industry during the course of the dual co-evolutionary development process as demonstrated in Table 1.

Table 1 suggests that new functionalities have steadily been assimilated into mobile phones through mutual learning [1] with such innovative products as televisions, video record/reproducers, digital cameras, video cameras, car navigation, and audio [4,5,8].

To date, while not a few studies have analyzed the dynamism inducing learning [14], effects of learning both by *learning by doing* and *learning by searching* [6,9,10,13], and also stimulating assimilation of technology [4,5], they have concentrated on macro aspects and are hardly satisfactory for analyzing co-evolutionary dynamism (a mutually inspiring virtuous cycle) as a consequence of learning between digital technologies. Williams et al. [22] postulated a concept of domestication which tames assimilated spillover technology for a whole institutional system in a co-evolutionary way. Watanabe et al. based on their analyses on dynamic learning coefficient [14,16] and also resonance [11], attempted to apply this concept in identifying the functionality development dynamism in mobile phones [17]. It was postulated that mobile phones attract a broad range of users by incorporating super-functionality, and users are not passive but producers of an exciting story with their own initiative that then thrills them with gratification of consumption. Therefore, upon being influenced by the excitement of mobile phones, users are transformed

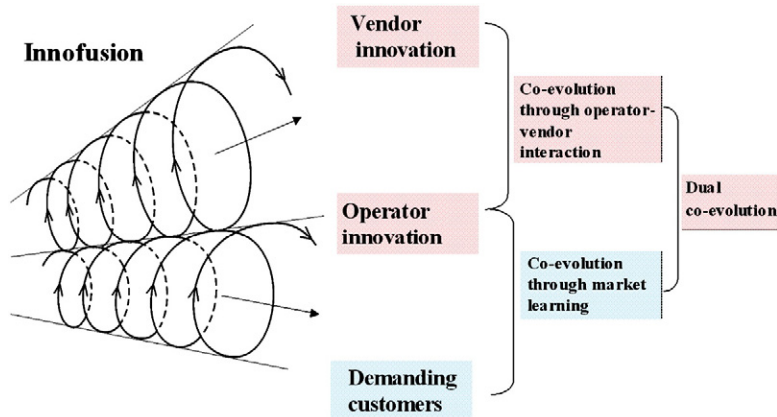


Fig. 2. Dual co-evolution in Japan's mobile phone development. Source: Chen and Watanabe [3].

Table 1

Chronology of functionality development acquirement by Japan's mobile phones (1993–2006).

Date	Functionality development
Mar 1993	Digital service
Oct 1997	e-mail transmission
Feb 1999	i-mode
Jul 1999	Infrared communications
Dec 1999	Color liquid crystal (LC)
Nov 2000	Camera function (stationary picture), music reproduction function
Dec 2000	Thin film transistor (TFT) LC
Oct 2001	Third-generation (3G) service
Feb 2002	GPS
Mar 2002	Camera function (animation), secure digital (SD) memory card
Dec 2003	FM radio, Analogue terrestrial TV tuner
Jul 2004	Noncontact IC card, Felica
Oct 2005	AM–FM TV radio
Dec 2005	One segment broadcasting (one seg)
Mar 2006	Organic EL display
May 2006	TV-brand mobile phone
Aug 2006	High speed packet access (HSDPA) communications
Dec 2006	Digital radio

into explorers in search of further exciting stories based on their own initiative and this then thrills them with gratification of such exploration. Fig. 3 demonstrates the functionality development dynamism in mobile phones.

This postulate may lead to constructive insight for identifying a possible new driver that will shape the new consumption structure in a post-global economic stagnation. However, details concerning the learning dynamism still remain a black box. This paper, on the basis of an empirical analysis of the learning dynamism for innovative products in Japan's digital industry, attempts to elucidate this dynamism.

Section 2 outlines the analytical framework. Empirical analysis on the learning dynamics of digital technology is presented in Section 3. Section 4 briefly summarizes new findings and policy implications.

2. Analytical framework

2.1. General framework of the analysis

General framework of the analysis can be decomposed into four parts as illustrated in Fig. 4.

First, trends in the magnitude of the effects of the learning in innovative products are analyzed by measuring dynamic learning coefficient of each respective product. Second, utilizing these trends, in order to identify the direction of the learning,

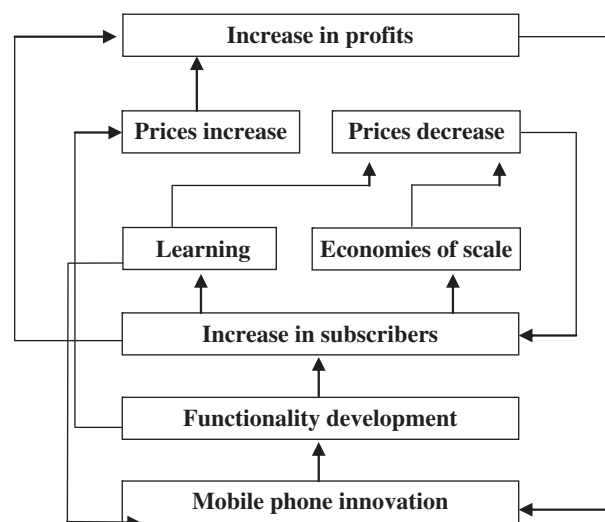


Fig. 3. Functionality development dynamism in mobile phones.
Source: Watanabe, Moriyama and Shin [17].

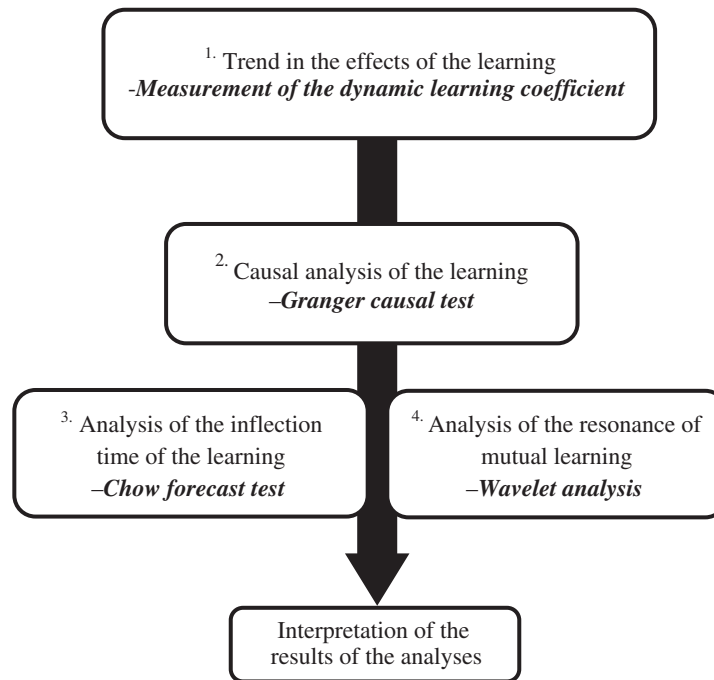


Fig. 4. Analytical framework.

causal analysis between changes in learning coefficients in innovative products is conducted. Third, inflection time of the learning in each respective product is analyzed for cross demonstration of the result of the causal analysis. Fourth, aiming at elucidating the sources of the learning dynamism, resonance of the learning between innovative products is analyzed. Based on these analyses as indicated in the second to the fourth analyses, learning dynamism between innovation products examined is identified.

2.2. Numerical analysis

2.2.1. Dynamic learning coefficient

Following Arrow's pioneer work [1], effect of the learning can be demonstrated as price decrease in line with the increase in cumulative production as depicted by the following equation with learning coefficient:

$$P = A \cdot Y^{*-\lambda} \quad (1)$$

$$\ln P = \ln A - \lambda \ln Y^* \quad (2)$$

where P : prices; A : scale factor; Y^* : cumulative production; and $\lambda (>0)$: learning coefficient.

Following Watanabe et al. [16,19], since learning coefficient is a function of successive coefficients during production, distribution and utilization phases in their dissemination process, these coefficients can be depicted by a function of time t as follows:

$$\lambda(t) = \lambda(\lambda_1(t), \lambda_2(t), \dots, \lambda_n(t)) \approx \sum_{i=0}^n a_i t^i \quad (3)$$

where $\lambda(t) (>0)$: dynamic learning coefficients at time t ; and a_i : coefficients of time trend t .

Thus, Eq. (2) can be developed as follows:

$$\ln P = \ln A - \lambda(t) \ln Y^* = \ln A - \sum_{i=0}^n a_i t^i \ln Y^* + \varepsilon \quad (4)$$

where P : prices; A : scale factor; Y^* : cumulative production; t : time trend; a_i : coefficients; and ε : error term.

By means of a regression analysis of Eq. (4), coefficients a_i , thereby dynamic learning coefficient $\lambda(t)$ can be identified (see details Appendix I).

2.2.2. Granger causal test

2.2.2.1. *Stationary test.* First, stationary state of time trend data should be examined. These data without trend are expected to satisfy the following three conditions:

$$\begin{aligned} \text{Average} \quad E[X_t] &= \mu \\ \text{Variance} \quad V[X_t] &= E[(X_t - \mu)^2] = \gamma(0) \\ \text{Auto covariance} \quad \text{Cov}(X_t, X_{t-s}) &= E[(X_t - \mu)(X_{t-s} - \mu)] = \gamma(s) \quad s = \dots -1, 0, 1, 2, \dots \end{aligned} \quad (5)$$

where X_t : random variable; μ : constant; and $\gamma(s)$: autocovariance function at s .

2.2.2.2. *Unit root test.* Stationary nature of the data can be examined by analyzing the auto-regression process of the data. Data with stationary nature satisfy $|\theta| < 1$ in Eq. (6). Generally, stationary state can be attained by d -th difference of the data as depicted in Eq. (7).

$$y_t = \theta y_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim i.i.d(0, \sigma^2) \quad (6)$$

where y_t : time series data at time t ; θ : coefficient; and ε_t : error term at time t .

$$y_t \sim I(d) \quad (7)$$

where y_t : time series data at time t ; and d : degree.

2.2.2.3. *Vector autoregression analysis.* Let y_1 depend on y_2 and y_1 in the preceding period, the following auto regression model can be obtained.

$$y_{1,t} = \alpha_1 + \alpha_2 y_{2,t} + \alpha_3 y_{1,t-1} + e_{1t} \quad (8)$$

where $y_{1,t}$: time series 1 data at time t ; $y_{2,t}$: time series 2 data at time t ; α_1 , α_2 , and α_3 : coefficients; and e_{1t} : error term at time t . Similarly, y_2 can be depicted by the following equation given it depends on y_1 and y_2 in the preceding period.

$$y_{2,t} = \beta_1 + \beta_2 y_{1,t-1} + \beta_3 y_{2,t-1} + e_{2t} \quad (9)$$

where $y_{1,t}$: time series 1 data at time t ; $y_{2,t}$: time series 2 data at time t ; β_1 , β_2 , and β_3 : coefficients; and e_{2t} : error term at time t .

These two equations depict dynamic correlation between y_1 and y_2 which leads to the following inducing multi-equations which can be depicted by the VAR (Vector Autoregression) model as Eq. (12).

$$y_{1,t} = \pi_{1,1} + \pi_{1,2} y_{1,t-1} + \pi_{1,3} y_{2,t-1} + v_{1t} \quad (10)$$

where $y_{1,t}$: time series 1 data at time t ; $y_{2,t}$: time series 2 data at time t ; $\pi_{1,1}$, $\pi_{1,2}$, and $\pi_{1,3}$: coefficients; and $v_{1,t}$: error term at time t .

$$y_{2,t} = \pi_{2,1} + \pi_{2,2} y_{1,t-1} + \pi_{2,3} y_{2,t-1} + v_{2t} \quad (11)$$

where $y_{1,t}$: time series 1 data at time t ; $y_{2,t}$: time series 2 data at time t ; $\pi_{2,1}$, $\pi_{2,2}$, and $\pi_{2,3}$: coefficients; and $v_{2,t}$: error term at time t .

$$y_t = v + \Theta y_{t-1} + u_t \quad (12)$$

$$y_t = \begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix} \quad v = \begin{bmatrix} \pi_{1,1} \\ \pi_{2,1} \end{bmatrix} \quad \Theta = \begin{bmatrix} \pi_{1,2} & \pi_{1,3} \\ \pi_{2,2} & \pi_{2,3} \end{bmatrix} \quad u_t = \begin{bmatrix} u_{1,t} \\ u_{2,t} \end{bmatrix}$$

where y_t : time series data at time t ; v and Θ : coefficients; $\pi_{1,1}$, $\pi_{1,2}$, $\pi_{1,3}$, $\pi_{2,1}$, $\pi_{2,2}$, and $\pi_{2,3}$: coefficients; and u_t : error terms at time t .

VAR model can be depicted by means of the following equations with error terms:

$$\begin{aligned} E[v_t] &= 0 \\ \text{COV}(v_t) = \Omega &= \begin{bmatrix} \omega_{11} & \omega_{12} \\ \omega_{21} & \omega_{22} \end{bmatrix} = \begin{bmatrix} V(v_{1t}) & \text{COV}(v_{1t}, v_{2t}) \\ \text{COV}(v_{2t}, v_{1t}) & V(v_{2t}) \end{bmatrix} \end{aligned} \quad (13)$$

where $v_{1,t}$ and $v_{2,t}$: error terms.

2.2.2.4. *Granger causal test.* Granger [7] developed a methodology to identify the cause and result relationship (Granger-cause) in the variables of the VAR model.

Let us consider the following VAR model with two preceding period impacts:

$$y_{1,t} = \pi_{1,1} + \pi_{1,2} y_{1,t-1} + \pi_{1,3} y_{2,t-1} + \pi_{1,4} y_{1,t-2} + \pi_{1,5} y_{2,t-2} + v_{1t} \quad (14)$$

where $y_{1,t}$: time series 1 data at time t ; $y_{2,t}$: time series 2 data at time t ; $\pi_{1,1}, \pi_{1,2}, \pi_{1,3}, \pi_{1,4}$, and $\pi_{1,5}$: coefficients; and $v_{1,t}$: error term at time t .

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix} = \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} + \begin{bmatrix} \pi_{11,1} & \pi_{12,1} \\ \pi_{21,1} & \pi_{22,1} \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \end{bmatrix} + \dots + \begin{bmatrix} \pi_{11,p} & \pi_{12,p} \\ \pi_{21,p} & \pi_{22,p} \end{bmatrix} \begin{bmatrix} y_{1,t-p} \\ y_{2,t-p} \end{bmatrix} + \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix} \tag{15}$$

where $y_{1,t}$: time series 1 data at time t ; $y_{2,t}$: time series 2 data at time t ; $\pi_{11,p}, \pi_{12,p}, \pi_{21,p}$, and $\pi_{22,p}$: coefficients at p ; and $u_{1,t}$ and $u_{2,t}$: error terms at time t .

Following conditions depicting y_2 does not Granger-cause y_1 and y_1 does not Granger-cause y_2 , respectively.

$$\pi_{12,1} = \pi_{12,2} = \dots = \pi_{12,p} = 0 \tag{16}$$

where $\pi_{11,p}$: coefficient at p .

$$\pi_{21,1} = \pi_{21,2} = \dots = \pi_{21,p} = 0 \tag{17}$$

where $\pi_{21,p}$: coefficient at p .

The null hypothesis that y_2 does not Granger-cause y_1 can be tested by the following F test.

$$F = \frac{(S_r - S_u)/p}{S_u/(T - 2p - 1)} \tag{18}$$

where F : F statistic; S_r : error sum of squares (unrestricted); S_u : error sum of squares (restricted); p : lag; and T : term.

2.2.3. Chow forecast test

Let the following time series data with time trend $t = 1, 2, 3, \dots, T$:

$$Y_t = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \dots + \beta_k X_{kt} + u_t \quad t = 1, \dots, T \tag{19}$$

where Y_t : time series data at time t ; X_{1t}, X_{2t}, \dots , and X_{kt} : time series data at time t ; β_k : coefficient at k ; and u_t : error term at time t .
F statistic for whole period $t = 1, 2, 3, \dots, T$ is depicted by Eq. (20)

$$F = \frac{S_r - S_u/k}{S_u/(T - 2k)} \tag{20}$$

F statistic for period dividing into period 1 ($t = 1, 2, \dots, T_1$) and 2 ($t = T_1 + 1, \dots, T$) is depicted by Eq. (21)

$$F = \frac{S_r - S_{u1}/T_2}{S_{u1}/(T_1 - 2k)} \tag{21}$$

where F : F statistic; S_r : error sum of squares (unrestricted); S_u : error sum of squares (restricted); k : lag; and T : term (T_1 : numbers of data between 1, 2, , ..., T_1 , and T_2 : numbers of data between $T_1 + 1, \dots, T$).

Inflection can be identified by rejecting the null hypothesis of parameter constancy if Eq. (21) exceeds Eq. (20).

2.2.4. Wavelet analysis

2.2.4.1. *The analyzing wavelet.* Wavelet analysis has attracted much attention recently in signal processing. Mathematically, the wavelet will resonate if the unknown signal contains information of similar frequency. This concept of resonance is at the core

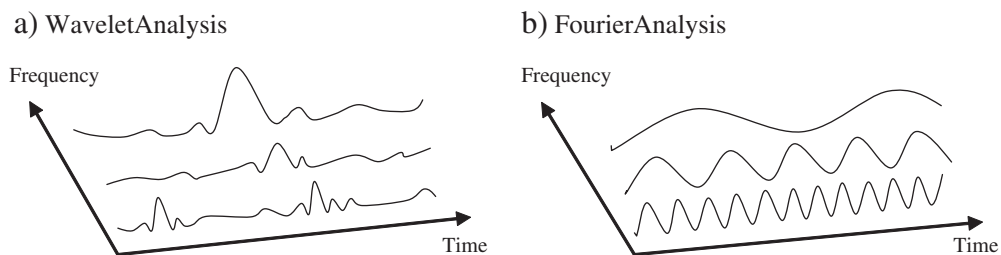


Fig. 5. Comparison of wavelet analysis and Fourier analysis.

of practical applications of wavelet theory. Therefore, wavelet analysis is used for the analysis of the resonance of the learning between innovative products.

Like Fourier analysis, wavelet analysis deals with expansion of functions in terms of a set basis functions. However, unlike Fourier analysis, wavelet analysis expands functions not in terms of trigonometric polynomials but in terms of wavelets, which are generated in the terms of transitions and dilations of a fixed function called the *mother wavelet* as compared in Fig. 5. Consequently, in signal processing, wavelets are very useful for processing nonstationary signals [12].

2.2.4.2. Continuous wavelet transform. Given the mother wavelet $\psi(t)$, wavelet function can be depicted by the following equation with parameters a and b :

$$\psi_{a,b}(t) \equiv \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right) \quad (22)$$

where t : variable; and a and b : parameters.

The parameter a corresponds to the scale of the analyzing wavelet indicating frequency by $1/a$ and the parameter b corresponds to the time shift.

Given $\hat{\psi}$ is the Fourier transform of ψ , following admissibility condition implying that if $\hat{\psi}(\omega)$ is smooth then $\hat{\psi}(0) = 0$ should be satisfied.

$$C_\psi = \int_{-\infty}^{\infty} \frac{|\hat{\psi}(\omega)|}{|\omega|} d\omega < \infty \quad (23)$$

where ω : variable; $\hat{\psi}$: Fourier transformation of ψ .

If ψ satisfies the conditions described above, then the wavelet transform of a real signal $f(x)$ with respect to the wavelet function $\psi(t)$ is defined as:

$$W(a, b) \equiv \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(x) \cdot \overline{\psi\left(\frac{x-b}{a}\right)} dx \quad (24)$$

where x : variable; a and b : parameters corresponding to the scale of the analyzing wavelet and the time scale, respectively, and $\overline{\psi}$ denotes the complex conjugate of ψ .

When function $\psi(t)$ satisfies the admissibility condition as depicted by Eq. (23), the original signal $f(x)$ can be obtained from the wavelet transform $W(a, b)$ by the following inverse formula:

$$f(x) \equiv \frac{1}{C_\psi} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} W(a, b) \cdot \frac{1}{\sqrt{a}} \psi\left(\frac{x-b}{a}\right) \frac{1}{a^2} da db \quad (25)$$

where x : variable; and a and b : parameters.

2.2.4.3. Discrete wavelet transform. In the discrete domain, the scale and shift parameters are described as $a = 2^m$ and $b = 2^m n$ in the continuous wavelet transform Eq. (22), and the analyzing wavelets are discretized as follows as a function of m and n :

$$\psi_{m,n}(t) = \frac{1}{\sqrt{2^m}} \psi(2^{-m}t - n) \quad (26)$$

where x : variable; and m and n : parameters.

The discrete wavelet transform and its inverse transform are defined as follows:

$$d_k^{(j)} \equiv 2^j \cdot \int_{-\infty}^{\infty} f(x) \cdot \overline{\psi(2^j x - k)} dx \quad (27)$$

where x : variable; and j and k : parameters.

$$h(x) = \sum_j \sum_k d_k^{(j)} \psi(2^j x - k) \quad (28)$$

where x : variable; and j and k : parameters.

2.3. Data construction

Monthly data of prices and cumulative production of seven innovative goods over the period January 2000–October 2007 were constructed.

Table 2

Dynamic learning coefficient in Japan's leading 7 innovation in electrical machinery (Jan. 2000–Oct. 2007).

<i>Mobile phones</i>	
$\ln P = 4.739 - (6.692 \times 10^{-3} + 4.904 \times 10^{-5} \cdot t^2 - 1.316 \times 10^{-6} \cdot t^3 + 3.763 \times 10^{-11} \cdot t^6$ $- 1.372 \times 10^{-12} \cdot t^7 + 2.028 \times 10^{-14} \cdot t^8 - 1.387 \times 10^{-16} \cdot t^9 + 3.634 \times 10^{-19} \cdot t^{10}) \cdot \ln Y^*$	$adj.R^2 = 0.998$
<i>Televisions</i>	
$\ln P = 5.565 - (7.909 \times 10^{-2} - 5.887 \times 10^{-3} \cdot t + 9.581 \times 10^{-5} \cdot t^2 - 7.321 \times 10^{-5} \cdot t^3 + 3.111 \times 10^{-6} \cdot t^4$ $- 7.853 \times 10^{-8} \cdot t^5 + 1.210 \times 10^{-9} \cdot t^6 - 1.119 \times 10^{-11} \cdot t^7 + 5.724 \times 10^{-14} \cdot t^8 - 1.247 \times 10^{-16} \cdot t^9) \cdot \ln Y^*$	$adj.R^2 = 0.998$
<i>Video record/reproducers</i>	
$\ln P = 5.625 - (7.158 \times 10^{-2} + 1.270 \times 10^{-3} \cdot t + 5.969 \times 10^{-5} \cdot t^2$ $- 2.382 \times 10^{-8} \cdot t^4 + 3.423 \times 10^{-10} \cdot t^5 - 1.476 \times 10^{-12} \cdot t^6) \cdot \ln Y^*$	$adj.R^2 = 0.996$
<i>Digital cameras</i>	
$\ln P = 5.064 - (2.886 \times 10^{-2} + 3.010 \times 10^{-5} \cdot t^2 - 3.495 \times 10^{-7} \cdot t^3 + 1.218 \times 10^{-9} \cdot t^4) \cdot \ln Y^*$	$adj.R^2 = 0.995$
<i>Video cameras</i>	
$\ln P = 6.127 - (1.145 \times 10^{-1} - 3.917 \times 10^{-3} \cdot t + 2.453 \times 10^{-4} \cdot t^2 - 6.359 \times 10^{-6} \cdot t^3$ $+ 9.056 \times 10^{-8} \cdot t^4 - 6.933 \times 10^{-10} \cdot t^5 + 2.208 \times 10^{-12} \cdot t^6) \cdot \ln Y^*$	$adj.R^2 = 0.995$
<i>Car navigation</i>	
$\ln P = 5.399 - (6.777 \times 10^{-2} - 2.419 \times 10^{-3} \cdot t + 1.411 \times 10^{-4} \cdot t^2$ $- 3.047 \times 10^{-6} \cdot t^3 + 2.887 \times 10^{-8} \cdot t^4 - 9.939 \times 10^{-11} \cdot t^5) \cdot \ln Y^*$	$adj.R^2 = 0.985$
<i>Audio</i>	
$\ln P = 5.375 - (5.248 \times 10^{-2} - 1.619 \times 10^{-3} \cdot t + 1.276 \times 10^{-4} \cdot t^2 - 4.303 \times 10^{-6} \cdot t^3$ $+ 7.408 \times 10^{-8} \cdot t^4 - 6.305 \times 10^{-10} \cdot t^5 + 2.096 \times 10^{-12} \cdot t^6) \cdot \ln Y^*$	$adj.R^2 = 0.977$

Seven innovative products encompass mobile phones, televisions, video record/reproducers, digital cameras, video cameras, car navigation, and audio.

Prices of these goods were based on Index of Production Prices by 2000 fixed price published by Bank of Japan (annual issues). Cumulative productions were based on number of subscribers of mobile phones published by Association of Telecommunication Enterprises (annual issues), and productions of innovative goods published in the Statistics of Dynamic Production by Ministry of Economy, Trade and Industry (annual issues). Depreciation rates of six innovative goods except mobile phones were estimated to 0.4–1.0% per month corresponding to 20–8 years of legal life time defined by the Corporate Tax Law while the rate of mobile phones was based on Fair Trade Commission of Japan [21].

Tables A1 and A2 in the Appendix II tabulate trends in prices and cumulative production of seven innovative products examined over the period Jan. 2000–Oct. 2007.

3. Empirical analysis

In line with the analytical framework outlined in the preceding section, an empirical analysis of the learning dynamics of Japan's leading innovation in electrical machinery over the period 2000–2007 was attempted.

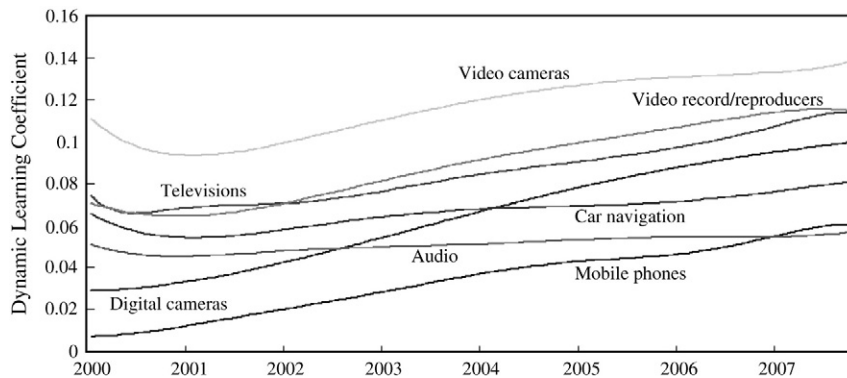


Fig. 6. Trends in dynamic leaning coefficient in Japan's leading 7 innovation in electrical machinery (Jan. 2000–Oct. 2007).

3.1. Dynamic learning coefficients

First, monthly dynamic learning coefficients in seven innovative goods over the period January 2000–October 2007 were estimated by means of the regression analysis on Eq. (4) with the criteria satisfying no multicollinearity, positive learning coefficient value, minimum AIC, and coefficient with 5% significant level.

The results of the regression analysis are summarized in Table 2. Looking at Table 2 we note that all coefficients demonstrate 1% significant level except fixed term learning coefficients of mobile phones and televisions as indicated * in t-value.

Fig. 6 demonstrated the trends in learning coefficients in seven innovative goods over the period Jan. 2000–Oct. 2007 (see Table A3 in the Appendix II estimated values). Looking at the Figure we note that contrary to other innovative goods as *video cameras*, *video record/reproducers*, *televisions*, *car navigation*, and *audio*, learning coefficients of *digital cameras* and *mobile phones* demonstrated consistent increase with higher increase rates than others over the whole period examined.

These trends suggest a possibility of co-evolutionary development between mobile phones and digital cameras by absorbing the learning effects of the advancement of relevant technologies [5,14].

3.2. Causality of learning between 7 innovative products

Prompted by the foregoing observation, the causality of learning between seven innovative products was analyzed. Prior to the causality analysis, in order to examine the stationary state of the trends in dynamic learning coefficient in these products, unit root test of the change rate of the learning coefficients was conducted. The results of the test are summarized in Table 3. Looking at the Table we note that all values tested indicate being statistically significant demonstrating the stationary state eligible to VAR model analysis.

With the confirmation of the stationary state of the learning coefficients of seven innovative products, Granger causal test was conducted by utilizing pair of time series estimated dynamic learning coefficient data as tabulated in Table A3. Result of the test of each respective pair of 7 innovative products is illustrated in Fig. 7.

The Figure demonstrates the significant comprehensive learning chain between seven innovative products. Noteworthy is that mobile phones absorb learning effects from all other innovative products and provide strong learning impact to digital cameras. Both correspond to author's preceding analyses that mobile phones absorbed learning effects of preceding innovation [17] and also Canon (leading digital camera producer) absorbed the effects of learning from mobile phones [11]. This observation suggests a possibility of mobile phones' strong absorptive power and co-evolution with digital cameras.

Table 3

Results of unit root test in 7 innovative products.

	t value	p value
Mobile phones	−8.81	0.000**
Televisions	−7.65	0.000**
Video record/reproducers,	−8.13	0.000**
Digital cameras	−10.8	0.000**
Video cameras	−7.03	0.000**
Car navigation	−7.49	0.000**
Audio	−7.41	0.000**

** Indicates significance at the 1% level.

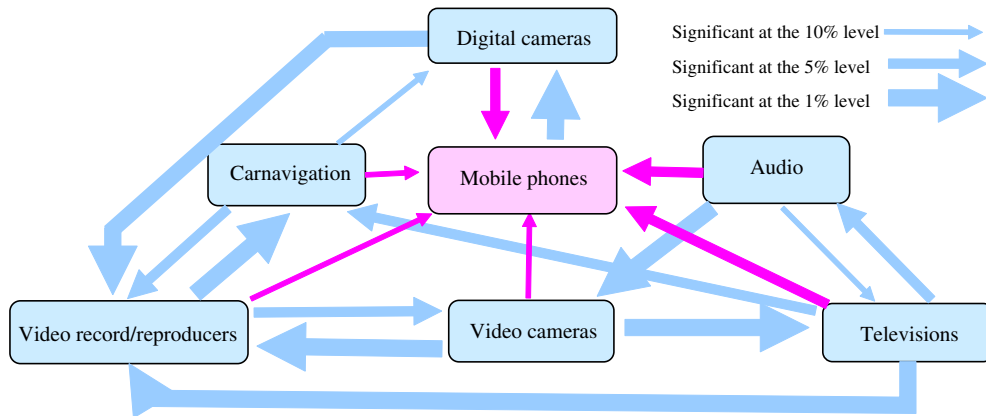


Fig. 7. Results of Granger causality test in 7 innovative products (Jan. 2000–Oct. 2007).

3.3. Structural change of learning

Prompted by the foregoing observation, aiming at demonstrating the above postulate, impacts of learning of respective innovative product on mobile phones were analyzed by tracing the structural change in learning coefficients. Fig. 8 illustrates the result of Chow forecast test of learning coefficient in seven innovative products over the period Jan. 2000–Oct. 2007. Higher level of the Figure demonstrates higher statistical significance corresponding to significant structural change with respect to respective learning coefficient.

Fig. 8 demonstrates three significant structural changes in mobile phones' learning coefficient during the period examined: *end of 2000–late 2001*, *beginning of 2002–middle 2003*, and *late 2005–end of 2006*. Looking at Fig. 1 and Table 1 we note that (i) camera function (stationary picture: Nov. 2000), music production function (Nov. 2000), thin film transistor (TFT) LC (Dec. 2000), and Third-generation (3G) service (Oct. 2001) were acquired by mobile phones during the first structural change period. Similarly, (ii) GPS (Feb. 2002), camera function (animation: Mar. 2002), and secure digital (SD) memory card (Mar. 2002), and (iii) AM–FM TV radio (Oct. 2005), one segment broadcasting (one seg: Dec. 2005), organic EL display (Mar. 2006), TV-brand mobile phone (May 2006), high speed packet access (HSDPA) communications (Aug. 2006), and digital radio (Dec. 2006) were acquired during the second and third structural change period, respectively. Fig. 8 also demonstrates significant structural change in digital cameras' learning coefficient during the period end of 2000–early 2002 corresponding to the installation of camera function both stationary picture (Nov. 2000) and animation (Mar. 2002) into mobile phones. Figs. 9 and 10 highlight this correspondence focusing on mobile phones and digital cameras. Fig. 9 reveals that the impacts of FM radio and analogue terrestrial TV tuner acquired in Dec. 2003 and also Non-contact IC card, Felica in Jul. 2004 on the structural change in mobile phones' learning were relatively small.

Fig. 9 demonstrates that mobile phones absorb learning effects from all other innovative products as *digital cameras*, *televisions*, *video record/reproducers*, *video cameras*, *car navigation* and *audio*. In addition, Fig. 10 demonstrates that mobile phones provide strong learning impact to digital cameras by incorporating their functions into mobile phones leading to a co-evolution between them. Incorporation of camera function (stationary picture) by J-Phone in Nov. 2000 has provided mobile phones significant learning from digital cameras enabling mobile phones' dramatic increase in their functions [3] which in turn induced digital cameras' significant learning from high functional mobile phones leading to developing animation camera function which is incorporated in mobile phones by NTT DoCoMo and au in Mar. 2002. Similar co-evolution can be observed also between video cameras and video record/reproducers, video record/reproducers and car navigation, and televisions and audio as suggested also by Fig. 7.

3.4. Resonance of learning

Prompted by such noting co-evolution typically observed between mobile phones and digital cameras, aiming at elucidating the sources of this co-evolutionary dynamism, wavelet analysis was attempted to learning coefficients of innovative products. Result of the analysis is illustrated in Figs. 11 and 12 by demonstrating trends in learning frequency of mobile phones and digital cameras over the period Jan. 2000–Apr. 2005.

The Figures demonstrate the learning frequency by spectrogram with logarithmic scale (*from high frequency (0) to low frequency (1.0)*).

Looking at the Figures we note that mobile phones demonstrate high frequency of learning during the period from the end of 2000 to the beginning of 2002 when camera function (stationary picture: Nov. 2000), music production function (Nov. 2000), thin film transistor (TFT) LC (Dec. 2000), third-generation (3G) service (Oct. 2001), GPS (Feb. 2002), camera function (animation: Mar. 2002), and secure digital (SD) memory card (Mar. 2002) were acquired. While digital cameras demonstrate high frequency of learning corresponding to camera functions of both stationary picture by J-Phone in Nov. 2000 and animation by NTT DoCoMo and au in Mar. 2002. Similar to Fig. 9, Fig. 11 also demonstrates that frequency of learning in acquiring FM radio and analogue terrestrial TV tuner (Dec. 2003) and also Noncontact IC card, Felica (Jul. 2004) was not so significant. All correspond to the analyses in Figs. 9 and 10.

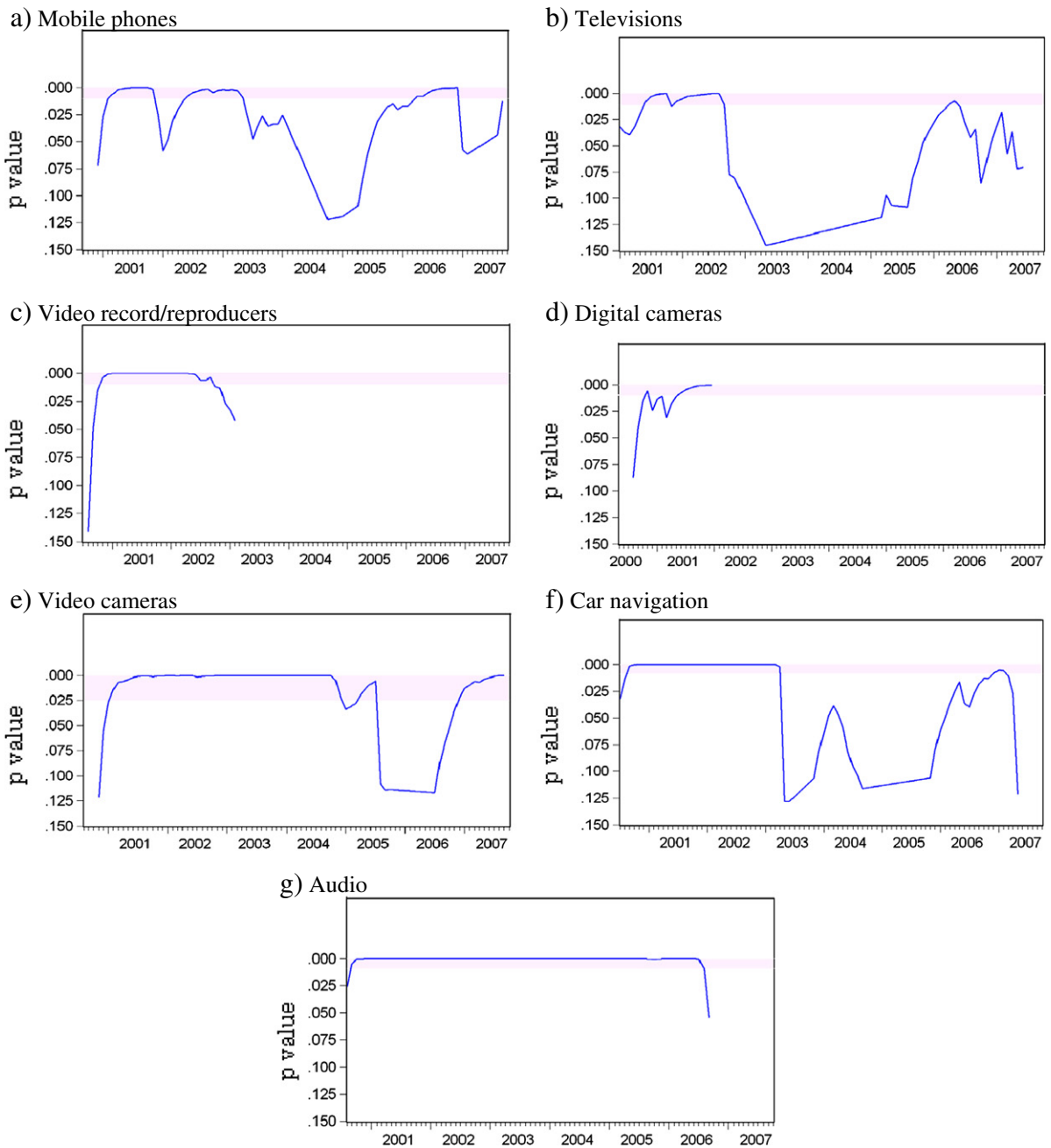


Fig. 8. Result of chow forecast test of learning coefficient in 7 innovative products (Jan. 2000–Oct. 2007).

As mentioned in Section 2, the wavelet will resonate if respective signals contain information of similar frequency. Similar high frequency observed both in mobile phones and digital cameras in sharing both stationary picture and animation camera functions in Nov. 2000 and Mar. 2002, respectively demonstrates this resonance. In order to incorporate own functions in mobile phones, digital camera made every endeavor for developing smaller, thinner, lighter, portable and durable functions. Induced by strong qualified requirements raised by mobile phones' demanding customers in a broad market, digital cameras accomplished a great functional development which incorporated into mobile phones leading them to their broad dissemination by learning digital cameras accomplishment. Since mobile phones acquire learning effects from broad innovation fields, learning from digital cameras synchronizes with effects of learning from broad innovation fields leading digital cameras further advancement which induces further incorporation in mobile phones. Thus, co-evolution between mobile phones advancement and that of digital cameras emerged. This co-evolution is triggered by the resonance between learning of mobile phones and digital cameras.

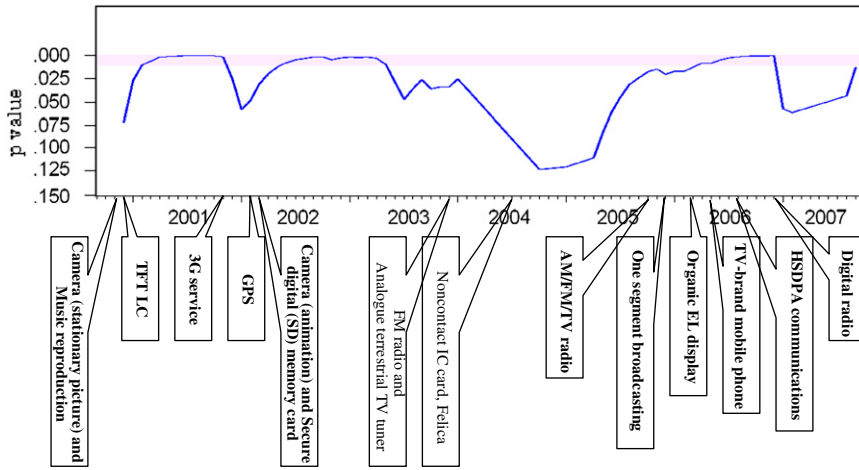


Fig. 9. Incorporation of new functions and corresponding learning structure change in mobile phones (Sep. 2000–Oct. 2007).

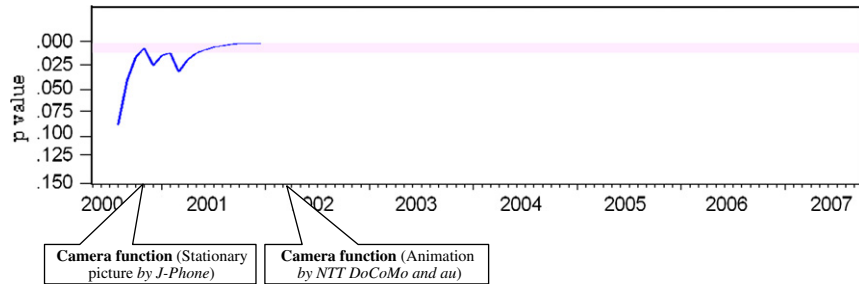


Fig. 10. Incorporation of new functions and corresponding learning structure change in digital cameras (May. 2000–Oct. 2007).

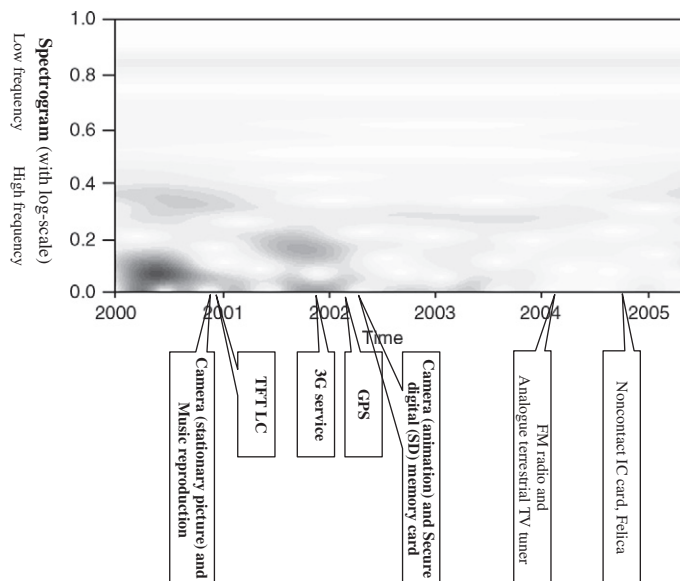


Fig. 11. Incorporation of new functions and corresponding learning frequency change in mobile phones (Jan. 2000–Apr. 2005).

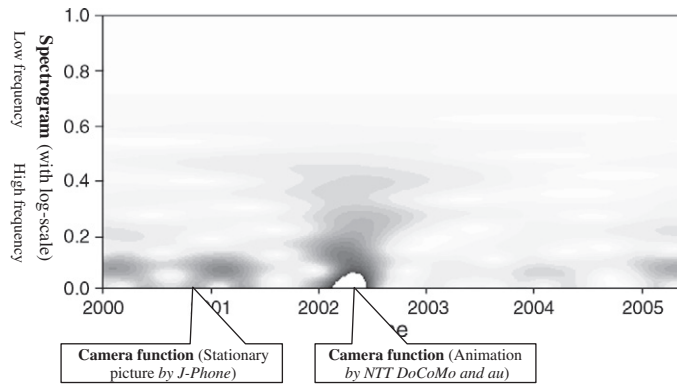


Fig. 12. Incorporation of new functions and corresponding learning frequency change in digital cameras (Jan. 2000–Apr. 2005).

Based on these analyses, we can conclude that coordinated by strong qualified requirements raised by mobile phones' demanding customers in a broad market, resonance between mobile phones learning and that of digital cameras triggered co-evolution between them leading to Japan's world conspicuous high-function mobile phones. This finding corresponds to our preceding finding that a dramatic deployment of Japan's high-function mobile phone service in the early 2000^s can be attributed to the resonance between information technology (IT) driven self-propagating trajectory and institutional spiral trajectory initiated by demanding customers in Japan's unique institutions with abundant curiosity, assimilation proficiency, thoroughness in learning and absorption as demonstrated in the clear contrast of degree of resonance measured by power spectral density by means of Fourier analysis illustrated in Fig. 13 [11].

4. Conclusion

In light of the increasing significance of a new driver instilling in customers an exciting story with their own initiative and thrills them with gratification of consumption during diminishing consumption after the simultaneous global economic stagnation, suggestion of Japan's high-functional mobile phone driven innovation is examined.

On the basis of an empirical analysis focusing on learning dynamism for innovative products in Japan's digital industry, the foregoing possibility was examined. Noteworthy findings include the following:

- (i) Based on the measurement of monthly dynamic learning coefficients for seven leading innovative products centered on mobile phones over the period of January 2000–October 2007, the Granger causal test, Chow forecast test and wavelet

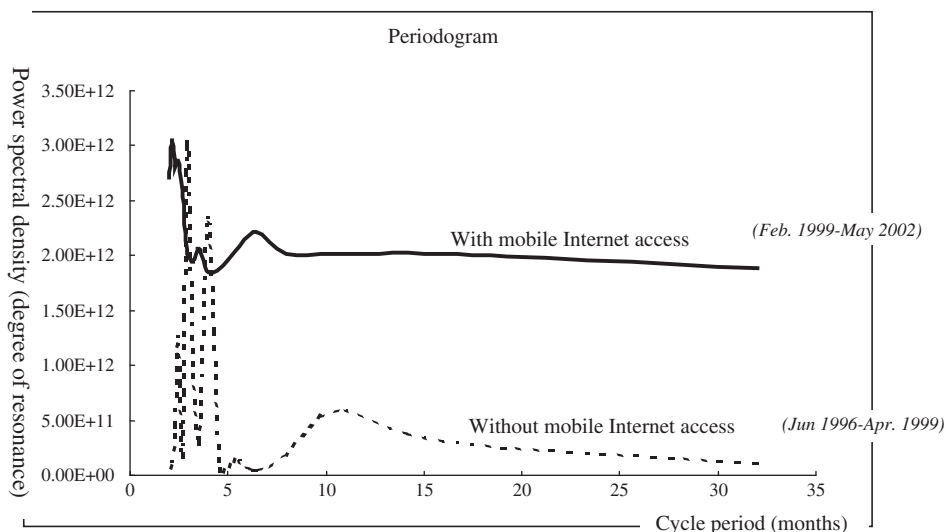


Fig. 13. Comparison of degree of resonance by power spectral density between mobile phones with and without internet access service. Source: Kondo, Watanabe and Moriyama [11].

analysis were conducted, and the significant role of mobile phones in leveraging broad dissemination, learning and absorption of core technologies essential to the advancement of digital industry was identified.

- (ii) Contrary to other innovative products, the learning coefficients of mobile phones and digital cameras demonstrated a consistent increase with a notable increase rate.
- (iii) The Granger causal test demonstrated that mobile phones absorbed learning from all innovative products and provided a learning impact to only digital cameras.
- (iv) The Chow forecast test identified structural change in learning coefficients in mobile phones and digital cameras corresponding to the incorporation of both stationary picture and animation camera functions in mobile phones.
- (v) A similar observation was also obtained by wavelet analysis demonstrating the high frequency of learning corresponding to the same incorporation, suggesting a significant resonance between mobile phone learning and that of digital cameras.
- (vi) This resonance triggered co-evolution between mobile phone advancement and that of digital cameras.
- (vii) Thus, it can be concluded that coordinated by strong qualified requirements raised by demanding mobile phone customers in a broad market, resonance between mobile phone learning and that of digital cameras triggered co-evolution between them leading to Japan's high-function mobile phones.

These findings provide insightful implications suggestive to firm technopreneurial strategy toward a post-simultaneous global economic stagnation society:

- (i) Resonance between signals emitted by innovation tempering consumption and signals emitted by consumers anticipating exciting innovation triggers co-emergence of innovation and consumption.
- (ii) Learning by both innovative products and consumers induces this resonance.
- (iii) Japan's unique institutional nature with abundant curiosity, assimilation proficiency and thoroughness in learning and absorption has leveraged consumer learning leading to co-evolutionary learning between mobile phones and consumers that triggers resonance between them.
- (iv) Therefore, institutional systems leveraging broad learning chains should be further cultivated and maintained.
- (v) This strategy corresponds to a new stream of technopreneurial strategy for open innovation in a global context and plays a role as a new driver instilling in customers an exciting story with their own initiatives and thrills them with gratification of consumption.

Further analysis should be undertaken for elucidation of the resonance dynamism between innovation and consumption.

Appendix I. Dynamic learning coefficient

Using relative price of production P and cumulative production Y^* , market learning in fusing global best practice can be depicted by the following function:

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

where A : scale factor and λ : learning coefficient.

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

$$\lambda = - \frac{\partial \ln P}{\partial \ln Y^*} \tag{A-2}$$

Since learning coefficient λ is a function of successive coefficients during production, distribution and utilization phases in their dissemination process as demonstrated in Fig. A1, these coefficients can be depicted as a function of time trend t as:

$$\lambda(t) = \lambda(\lambda_1(t), \lambda_2(t), \lambda_3(t), \dots, \lambda_n(t)) \approx \sum_{i=0}^n a_i t^i \tag{A-3}$$

where a_i is the coefficient of time trend t .

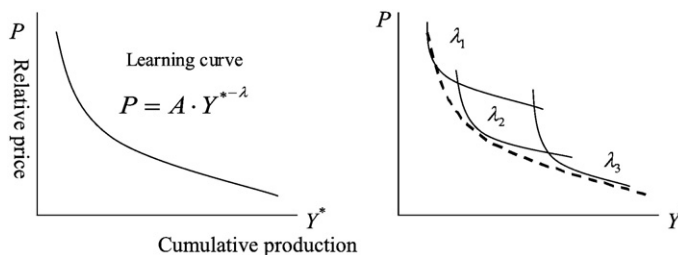


Fig. A-1. Concept of successive learning.

Dynamic learning coefficients $\lambda_1, \lambda_2 \dots \lambda_n$ depict learning effects in a serial process of production, distribution and utilization as effects of market learning including education (x_1), experience (x_2), innovation (x_3) and other effects contributing to improve productivity, and can be enumerated as follows:

$$\lambda_i = \lambda_i(x_1, x_2, x_3, \dots) i = 1, 2, \dots, n.$$

Substitute $\lambda(t)$ depicted in Eq. (A-3) for λ in Eq. (A-1), and take logarithms, the following equation can be obtained:

$$\ln P = \ln A - \sum_{i=0}^n a_i t^i \cdot \ln Y^* + \varepsilon \quad (\text{A-4})$$

where ε is disturbance term which is independent from $\lambda(t)$.

Taking differentiation of Eq. (A-4) by $\ln Y^*$, $\lambda(t)$ can be computed as follows:

$$\lambda(t) = -\frac{\partial \ln P}{\partial \ln Y^*} = \sum_{i=0}^n a_i t^i + \ln Y^* \frac{\partial \sum_{i=0}^n a_i t^i}{\partial \ln Y^*} \approx \sum_{i=0}^n a_i t^i. \quad (\text{A-5})$$

Appendix II. Trends in prices, cumulative production and estimated dynamic learning coefficients of 7 innovative goods (Jan. 2000–Oct. 2007)

Table A1

Trends in prices of 7 innovative products – Index, 2000 = 100 (Jan.2000–Oct.2007).

	Mobile phones and PHS Phone	Televisions	Video record/reproducers	Video cameras	Digital cameras	Car navigation	Audio
<i>(2000 average = 100)</i>							
Jan-00	104.1	103.5	104.6	101.7	113.5	100.7	101.8
Feb-00	103.9	102.7	103.5	100.6	106.9	100.7	101.8
Mar-00	103.9	102.7	103.5	100.6	103.7	100.7	101.3
Apr-00	102.3	102.7	101.7	97.9	103.7	100.7	101.3
May-00	102.3	102.5	101.7	97.9	99.6	100.7	101.3
Jun-00	100.7	101.8	99.6	100.9	98.9	100.7	100.9
Jul-00	98.2	99.9	99.1	100.9	97.5	99.9	99.9
Aug-00	98.2	98.1	97.5	100.9	97.5	99.2	99.4
Sep-00	97.3	97.5	97.5	100.4	97.5	99.2	98.7
Oct-00	97.3	96.2	97.2	100.4	96.1	99.2	97.9
Nov-00	96.8	96.1	97	99.3	91.8	99.2	97.9
Dec-00	95.3	96.3	97	98.7	93.2	98.8	97.9
Jan-01	94.4	93.7	97	98.1	90.3	97.7	97.9
Feb-01	92.5	93.1	96.2	97.5	89.1	97.7	97.9
Mar-01	91.8	91.4	96.2	96	91.5	97.7	97.8
Apr-01	90.1	89.8	94.9	95.4	86.8	97	97.8
May-01	88.8	88.6	93.7	95.4	86.4	95.6	97.2
Jun-01	88.2	88.2	93.7	95.5	85.7	93.7	96.5
Jul-01	88.2	87.6	93.7	94.3	84.9	92.1	95.9
Aug-01	87.6	87	93.1	92.8	84.7	92.1	95.6
Sep-01	83.9	86.8	91.6	91.8	84	92.1	95.6
Oct-01	83.5	89.7	91.3	91.8	84	92.1	95.6
Nov-01	83.5	88.8	90.9	90.8	86.2	92.1	95.6
Dec-01	83.5	88	89.6	90.8	84.2	92.1	92.4
Jan-02	81	87.8	87.8	86.1	84.2	92.1	92.1
Feb-02	81	86.7	87.8	85.3	83.4	92.1	91.2
Mar-02	79.9	83.5	86	84.3	82.4	91.1	90.9
Apr-02	78.5	83	83.7	81.2	66.6	87.3	90.9
May-02	78.2	82.2	76.6	80.8	65.6	86.5	90.6
Jun-02	77.5	82.4	76.6	80.8	64.2	84.2	89.9
Jul-02	77.5	82.2	76.6	74.3	64.7	84.2	89.9
Aug-02	75.5	80.7	76.1	74.3	65.5	83.5	89.5
Sep-02	73.4	80.6	76.1	73.5	64.5	83.5	89.5
Oct-02	70.8	80.9	73.1	70.9	63.2	83.5	89
Nov-02	70.7	78.6	73.1	70.3	62.5	83.5	88.3
Dec-02	69.8	78.3	71.7	68.4	62.7	83.5	87.2
Jan-03	69.8	78.3	71.7	68.4	60.8	83.5	87.2
Feb-03	69.8	75.3	71.4	65.2	60.7	81	85.7
Mar-03	69.8	74.1	68.3	65.2	57.9	81	85.2
Apr-03	66.9	73.2	65.1	61.8	55.3	77.1	85.2

Table A1 (continued)

	Mobile phones and PHS Phone	Televisions	Video record/reproducers	Video cameras	Digital cameras	Car navigation	Audio
<i>(2000 average = 100)</i>							
May-03	66.7	71.9	62.4	62	55.3	70.7	85.3
Jun-03	66.3	71.1	63.3	61.2	53.9	73.9	85
Jul-03	66.3	70.8	62.6	60.4	53.9	73.9	85.3
Aug-03	65.3	69.2	62.8	59.4	53.9	73.9	85.2
Sep-03	62.6	68.8	60.4	59.4	52.9	73.9	84.7
Oct-03	61.8	67.1	60.5	57.9	52.2	72	84.9
Nov-03	60.4	66.2	61.2	57.3	47.8	72	84.9
Dec-03	60.2	66.2	60.8	57.3	47.8	71.7	84.9
Jan-04	61	65	60.1	57.7	47.8	71.5	84.9
Feb-04	60.9	64.4	59.7	56	45.8	72.2	84.9
Mar-04	59.6	64.8	58.6	55.5	45.8	72.1	84.7
Apr-04	57.4	64.1	58	54.1	42.8	71.3	84.7
May-04	56.9	63	53.5	54.1	43	71.1	84.7
Jun-04	56.8	63	53.4	52.1	43	70.7	84.7
Jul-04	56.4	62.1	55.2	49.1	41.9	70.8	84.8
Aug-04	56.3	61	55.1	48.8	41.4	71	84.8
Sep-04	56.3	59.4	54.1	48.8	41.2	71	84.8
Oct-04	56.1	60	51.7	48.8	40.3	69.7	84.1
Nov-04	54.1	60	50.1	48.8	40.7	70	82.6
Dec-04	53.7	57.3	51.9	48.8	39.9	69.4	82.7
Jan-05	53.2	57.3	50.9	48.4	35.2	68.2	82.7
Feb-05	53.5	56.6	49.4	47.9	36.5	69.6	82.8
Mar-05	53.5	56.9	50.4	47.9	36.1	70.1	79
Apr-05	53.2	56.6	48.8	47.1	34.5	70.4	78.7
May-05	53.2	56	48.8	47.1	34.4	70.7	78.7
Jun-05	53	54.6	48.8	47.1	34.4	68.2	78.7
Jul-05	53	54.4	48.7	46.7	34.2	68.2	78.7
Aug-05	53	54	47.3	42.1	33.6	68	78.8
Sep-05	52.1	53.7	45.5	41.8	33.6	67.2	78.7
Oct-05	51	52.5	45.3	42.8	33.3	67.3	78.7
Nov-05	50.8	51.9	43.8	44.5	31.2	67.2	78.1
Dec-05	50.8	51.6	44.3	44.5	31.2	67.4	78.2
Jan-06	50.2	51.3	44.5	43.1	30.6	67.5	78.1
Feb-06	50.2	49.7	43.2	43.1	30.6	67.9	78.1
Mar-06	50	49.4	42.6	42.1	30.5	67.5	80.4
Apr-06	49.6	47.4	41.8	42.4	29.7	67.1	80.5
May-06	48	46.3	41.2	42.2	28.4	66.2	80.4
Jun-06	48	45.8	41.2	42.2	28.7	62.4	80.4
Jul-06	47.3	45.5	41.2	41.1	28.5	61.6	80.5
Aug-06	46.9	45.4	40.7	41.1	27	61.5	79.7
Sep-06	46.9	45.3	40.4	40.5	26.9	61.5	79.7
Oct-06	45.1	42.9	40.2	41.7	26.6	60.9	79.8
Nov-06	45.4	42.2	39.9	41.7	26.5	60.9	79.8
Dec-06	44.9	42.1	39.5	41.3	26.4	57.7	79.3
Jan-07	40.8	42	39.2	41.3	26.2	57.7	79.2
Feb-07	41.4	41.5	37.9	40.6	25.8	57.7	78.3
Mar-07	41.4	39.5	37.8	40.6	25.6	57.7	78.4
Apr-07	41.4	39	38.2	39.5	25.3	57.6	77.8
May-07	40.4	36.7	39.2	39.5	25.3	58	77.8
Jun-07	40.2	36.7	38.2	38.8	25.3	57.5	77.5
Jul-07	39.5	36.6	37.9	38.8	24.8	56	77.3
Aug-07	39.8	36.6	37.7	38.8	24.8	56	76.9
Sep-07	39.8	36.6	37.7	38.4	23.5	56	76.9
Oct-07	38.2	36.4	37.7	33.7	22.8	55.9	75.9

Table A2

Trends in cumulative production of 7 innovative products (Jan.2000–Oct.2007).

	Mobile phones	Televisions	Video record/reproducers	Digital cameras	Video cameras	Car navigation	Audio
Jan-00	627,300	274,007	804,624	438,726	691,492	116,052	2,016,389
Feb-00	1,393,200	547,546	1,684,933	817,276	1,485,501	259,940	4,453,048
Mar-00	2,665,700	867,233	2,682,095	1,383,081	2,402,152	455,220	7,219,502
Apr-00	3,809,800	1,112,081	3,505,088	1,999,599	3,271,253	626,140	9,500,117
May-00	4,471,300	1,358,786	4,371,317	2,715,816	4,307,912	830,362	11,695,602
Jun-00	5,248,000	1,652,556	5,303,162	3,583,265	5,429,249	1,084,327	14,333,183

(continued on next page)

Table A2 (continued)

	Mobile phones	Televisions	Video record/reproducers	Digital cameras	Video cameras	Car navigation	Audio
Jul-00	6,022,300	1,913,640	6,348,419	4,365,060	6,518,547	1,327,944	17,192,941
Aug-00	6,662,200	2,145,916	7,231,359	5,257,834	7,563,973	1,523,139	19,518,582
Sep-00	7,397,700	2,399,382	8,022,929	6,252,616	8,749,351	1,741,584	22,130,835
Oct-00	7,990,900	2,686,521	8,774,294	7,445,583	9,951,805	1,969,496	24,550,505
Nov-00	8,640,600	2,979,260	9,482,414	8,670,251	11,037,107	2,233,656	26,859,050
Dec-00	9,711,800	3,341,726	10,059,650	9,615,968	11,705,804	2,447,695	29,089,924
Jan-01	10,437,600	3,542,539	10,385,817	10,311,739	12,288,198	2,610,864	30,991,398
Feb-01	11,166,000	3,783,436	10,873,836	10,945,988	12,894,449	2,792,380	32,953,150
Mar-01	12,661,300	4,041,605	11,353,697	11,674,602	13,640,908	3,025,142	35,241,766
Apr-01	13,757,400	4,285,320	11,794,424	12,564,808	14,551,272	3,226,821	37,111,154
May-01	14,412,700	4,537,203	12,195,315	13,751,855	15,351,383	3,501,031	39,012,614
Jun-01	15,115,100	4,808,724	12,514,367	14,954,403	16,100,401	3,824,054	41,076,953
Jul-01	15,906,500	5,020,099	12,949,377	16,117,419	16,939,662	4,102,465	43,179,080
Aug-01	16,444,000	5,227,916	13,367,888	17,105,561	17,636,860	4,300,231	44,951,631
Sep-01	17,089,400	5,440,582	13,856,529	18,524,725	18,390,691	4,502,886	47,042,578
Oct-01	17,652,400	5,704,570	14,396,931	20,169,770	19,226,788	4,762,136	49,203,246
Nov-01	18,126,100	5,978,177	14,822,188	21,560,414	19,835,028	5,037,493	51,048,978
Dec-01	18,839,800	6,259,555	15,198,328	22,400,527	20,227,891	5,252,745	52,906,208
Jan-02	19,279,700	6,476,775	15,514,038	23,031,905	20,678,522	5,415,200	54,256,163
Feb-02	19,749,300	6,743,916	15,765,257	23,711,725	21,414,487	5,620,847	55,734,009
Mar-02	20,873,500	6,997,623	16,130,594	24,635,380	22,174,182	5,840,062	57,517,654
Apr-02	21,524,300	7,209,493	16,416,327	25,677,825	22,982,908	6,048,115	59,136,905
May-02	21,950,500	7,485,557	16,694,286	26,826,501	23,855,336	6,313,926	60,839,635
Jun-02	22,472,300	7,740,254	17,002,555	28,246,318	24,644,953	6,595,520	62,594,930
Jul-02	23,004,300	7,979,253	17,348,723	29,799,291	25,537,063	6,905,824	64,570,716
Aug-02	23,387,000	8,217,491	17,664,584	31,279,840	26,207,626	7,129,179	66,021,469
Sep-02	23,855,600	8,510,573	18,013,711	33,025,210	26,992,787	7,384,664	67,558,708
Oct-02	24,224,300	8,827,643	18,444,072	35,134,018	27,966,925	7,691,407	69,328,125
Nov-02	24,592,100	9,174,205	18,797,058	37,442,592	28,778,499	8,018,222	71,059,474
Dec-02	25,299,100	9,486,212	19,099,331	39,316,778	29,220,918	8,280,043	72,605,921
Jan-03	25,692,800	9,644,698	19,338,634	40,823,810	29,621,748	8,509,984	73,425,887
Feb-03	26,170,700	9,824,260	19,564,053	42,106,995	30,267,251	8,809,770	74,375,208
Mar-03	27,469,000	10,016,360	19,746,039	43,884,382	31,266,292	9,108,707	75,475,206
Apr-03	28,130,900	10,230,082	20,009,860	45,477,398	32,306,891	9,409,543	76,565,263
May-03	28,553,000	10,481,134	20,302,111	47,422,302	33,332,556	9,780,326	77,564,278
Jun-03	29,050,500	10,722,887	20,564,647	49,538,119	34,196,811	10,174,429	78,631,942
Jul-03	29,645,500	10,944,140	20,890,991	51,404,668	35,044,747	10,530,139	79,845,199
Aug-03	30,079,500	11,178,908	21,150,684	52,961,521	35,983,059	10,763,240	80,729,637
Sep-03	30,457,900	11,510,948	21,490,967	55,594,098	37,473,940	11,055,286	81,802,965
Oct-03	30,827,300	11,864,232	21,825,989	58,683,170	38,739,592	11,420,071	83,052,102
Nov-03	31,167,200	12,198,095	22,242,760	61,720,802	39,777,393	11,782,170	84,084,247
Dec-03	31,681,000	12,536,170	23,094,454	64,401,227	40,475,234	12,114,374	85,195,505
Jan-04	32,030,500	12,752,899	23,274,110	66,234,422	41,023,012	12,408,078	85,966,033
Feb-04	32,030,500	13,013,102	23,444,099	67,929,023	42,016,060	12,762,469	86,808,402
Mar-04	32,030,500	13,310,093	23,722,821	70,088,550	43,578,272	13,158,112	87,648,173
Apr-04	33,942,400	13,582,259	24,021,218	72,183,025	44,849,751	13,553,948	88,471,005
May-04	34,271,500	13,869,258	24,207,354	74,590,401	45,925,077	13,921,767	88,998,269
Jun-04	34,664,600	14,190,139	24,475,848	77,224,881	46,921,472	14,370,486	89,445,208
Jul-04	35,115,200	14,530,071	24,766,583	79,553,278	47,765,344	14,808,234	89,931,505
Aug-04	35,443,400	14,799,929	24,985,144	81,596,305	48,663,363	15,120,382	90,343,375
Sep-04	35,837,500	15,076,692	25,274,221	84,468,651	49,737,766	15,530,429	90,914,840
Oct-04	36,190,000	15,366,067	25,596,895	87,866,272	50,852,351	15,936,680	91,440,528
Nov-04	36,503,200	15,688,159	25,889,240	91,468,797	51,865,086	16,403,600	91,928,078
Dec-04	37,008,600	16,020,251	26,308,213	93,600,982	52,431,748	16,821,204	92,466,671
Jan-05	37,299,500	16,234,473	26,413,537	95,307,786	53,212,049	17,188,593	92,736,863
Feb-05	37,667,100	16,531,965	26,516,907	97,322,348	54,300,297	17,596,504	93,052,365
Mar-05	38,522,400	16,879,223	26,657,761	99,780,925	55,474,783	18,087,324	93,339,129
Apr-05	38,960,100	17,243,380	26,864,902	102,205,403	56,782,061	18,518,277	93,600,455
May-05	39,269,000	17,644,891	27,041,846	104,361,329	57,832,482	18,962,829	93,772,626
Jun-05	39,600,400	18,081,972	27,242,154	106,550,140	58,865,837	19,467,780	93,963,363
Jul-05	40,060,800	18,498,389	27,450,809	108,587,718	59,892,861	19,955,937	94,105,479
Aug-05	40,357,100	18,931,822	27,608,631	110,521,970	60,993,885	20,342,424	94,249,418
Sep-05	40,651,600	19,388,182	27,753,307	113,467,605	62,299,563	20,788,391	94,405,461
Oct-05	40,890,000	19,897,169	27,960,947	116,710,357	63,663,178	21,242,280	94,549,025
Nov-05	41,203,700	20,512,883	28,251,646	120,167,865	64,872,544	21,744,240	94,687,570
Dec-05	41,702,600	21,182,984	28,540,708	122,476,865	65,507,329	22,186,656	94,831,639
Jan-06	41,957,800	21,585,883	28,640,336	124,453,383	66,385,218	22,565,839	94,906,703
Feb-06	42,292,500	22,071,346	28,731,845	126,609,624	67,486,283	22,983,010	94,960,969
Mar-06	43,316,800	22,646,360	28,858,453	129,228,499	68,479,818	23,496,760	95,017,177
Apr-06	43,796,900	23,228,291	29,035,170	132,191,377	69,559,704	23,955,313	95,063,500

Table A2 (continued)

	Mobile phones	Televisions	Video record/reproducers	Digital cameras	Video cameras	Car navigation	Audio
May-06	44,080,500	23,795,025	29,161,166	135,260,583	70,634,566	24,400,066	95,097,008
Jun-06	44,394,100	24,379,655	29,307,471	138,335,085	71,568,618	24,896,207	95,140,190
Jul-06	44,777,900	24,877,305	29,456,880	140,959,183	72,472,322	25,352,353	95,190,619
Aug-06	45,026,700	25,311,829	29,578,064	143,994,684	73,462,560	25,729,568	95,227,645
Sep-06	45,337,200	25,884,290	29,769,702	148,000,697	74,774,642	26,143,754	95,269,961
Oct-06	45,602,400	26,629,047	30,025,053	152,562,510	76,138,701	26,564,957	95,334,058
Nov-06	45,978,500	27,460,487	30,266,329	156,855,370	77,384,817	27,069,381	95,391,624
Dec-06	46,460,700	28,248,183	30,586,719	159,627,026	78,031,689	27,519,157	95,467,652
Jan-07	46,840,000	28,714,659	30,661,744	161,496,692	78,713,414	27,922,344	95,503,198
Feb-07	47,287,100	29,283,550	30,740,684	164,148,215	79,735,978	28,337,166	95,539,693
Mar-07	48,242,700	29,939,677	30,835,416	167,475,759	81,178,942	28,803,248	95,571,052
Apr-07	48,721,600	30,646,094	30,951,455	171,669,691	82,502,003	29,270,734	95,591,885
May-07	49,105,100	31,290,672	31,070,616	175,682,557	83,557,402	29,784,685	95,613,782
Jun-07	49,580,600	31,937,817	31,192,460	179,499,461	84,525,657	30,311,957	95,632,795
Jul-07	50,078,000	32,576,032	31,293,210	183,155,518	85,382,316	30,839,079	95,648,365
Aug-07	50,402,500	33,228,164	31,374,871	186,814,290	86,319,148	31,277,410	95,659,299
Sep-07	50,858,400	33,882,957	31,455,454	191,840,941	87,491,192	31,692,801	95,685,126
Oct-07	51,189,900	34,803,371	31,628,448	198,112,713	88,880,204	32,216,739	95,701,589

Table A3

Trends in estimated dynamic learning coefficient of 7 innovative products (Jan.2000–Oct.2007).

	Mobile phones	Televisions	Video record/reproducers	Digital cameras	Video cameras	Car navigation	Audio
Jan-00	0.00674	0.07409	0.07037	0.02889	0.11078	0.06549	0.05099
Feb-00	0.00688	0.07061	0.06928	0.02898	0.10755	0.06348	0.04972
Mar-00	0.0071	0.06831	0.06831	0.02912	0.10475	0.06171	0.04866
Apr-00	0.00739	0.06691	0.06745	0.02932	0.10233	0.06017	0.04779
May-00	0.00775	0.06618	0.06671	0.02957	0.10026	0.05884	0.04708
Jun-00	0.00817	0.06593	0.06608	0.02987	0.09852	0.05771	0.04652
Jul-00	0.00865	0.06601	0.06556	0.03022	0.09708	0.05677	0.04609
Aug-00	0.00916	0.0663	0.06516	0.03061	0.09591	0.056	0.04578
Sep-00	0.00972	0.06672	0.06485	0.03105	0.09499	0.05539	0.04556
Oct-00	0.01031	0.06719	0.06465	0.03153	0.0943	0.05492	0.04543
Nov-00	0.01092	0.06767	0.06454	0.03206	0.09381	0.05458	0.04537
Dec-00	0.01155	0.06812	0.06452	0.03262	0.0935	0.05436	0.04538
Jan-01	0.0122	0.06853	0.0646	0.03322	0.09337	0.05426	0.04544
Feb-01	0.01286	0.06888	0.06476	0.03385	0.09338	0.05425	0.04554
Mar-01	0.01353	0.06917	0.065	0.03452	0.09352	0.05433	0.04568
Apr-01	0.0142	0.0694	0.06532	0.03522	0.09379	0.05448	0.04585
May-01	0.01487	0.06959	0.0657	0.03595	0.09416	0.05471	0.04604
Jun-01	0.01554	0.06973	0.06616	0.0367	0.09463	0.055	0.04625
Jul-01	0.01622	0.06984	0.06667	0.03749	0.09517	0.05535	0.04647
Aug-01	0.01689	0.06994	0.06725	0.0383	0.09579	0.05574	0.04669
Sep-01	0.01755	0.07004	0.06787	0.03914	0.09647	0.05617	0.04692
Oct-01	0.01822	0.07014	0.06855	0.03999	0.09721	0.05663	0.04715
Nov-01	0.01888	0.07027	0.06927	0.04087	0.09799	0.05712	0.04738
Dec-01	0.01954	0.07042	0.07003	0.04177	0.0988	0.05763	0.04761
Jan-02	0.0202	0.07061	0.07082	0.04269	0.09965	0.05816	0.04783
Feb-02	0.02086	0.07085	0.07164	0.04362	0.10053	0.05869	0.04804
Mar-02	0.02152	0.07113	0.07249	0.04457	0.10142	0.05924	0.04824
Apr-02	0.02218	0.07146	0.07336	0.04554	0.10233	0.05978	0.04844
May-02	0.02285	0.07184	0.07425	0.04651	0.10325	0.06032	0.04863
Jun-02	0.02352	0.07227	0.07516	0.0475	0.10418	0.06086	0.0488
Jul-02	0.0242	0.07275	0.07607	0.0485	0.10511	0.06139	0.04897
Aug-02	0.02489	0.07328	0.077	0.04951	0.10604	0.06191	0.04913
Sep-02	0.02559	0.07385	0.07793	0.05052	0.10697	0.06241	0.04929
Oct-02	0.02629	0.07445	0.07886	0.05155	0.10789	0.0629	0.04943
Nov-02	0.027	0.07509	0.07979	0.05257	0.10881	0.06338	0.04957
Dec-02	0.02772	0.07576	0.08071	0.05361	0.10971	0.06383	0.04971
Jan-03	0.02845	0.07645	0.08163	0.05465	0.11061	0.06427	0.04984
Feb-03	0.02919	0.07715	0.08254	0.05569	0.1115	0.06468	0.04996
Mar-03	0.02993	0.07786	0.08345	0.05673	0.11237	0.06507	0.05009
Apr-03	0.03068	0.07858	0.08434	0.05777	0.11324	0.06544	0.05021
May-03	0.03142	0.07929	0.08522	0.05881	0.11408	0.06579	0.05033
Jun-03	0.03217	0.08	0.08608	0.05985	0.11491	0.06612	0.05045
Jul-03	0.03292	0.0807	0.08693	0.06089	0.11573	0.06643	0.05057

(continued on next page)

Table A3 (continued)

	Mobile phones	Televisions	Video record/reproducers	Digital cameras	Video cameras	Car navigation	Audio
Aug-03	0.03366	0.08138	0.08776	0.06192	0.11653	0.06671	0.05069
Sep-03	0.03439	0.08205	0.08858	0.06296	0.11731	0.06697	0.05081
Oct-03	0.03511	0.0827	0.08938	0.06398	0.11807	0.06722	0.05094
Nov-03	0.03581	0.08333	0.09016	0.06501	0.11882	0.06744	0.05107
Dec-03	0.0365	0.08394	0.09092	0.06602	0.11955	0.06765	0.0512
Jan-04	0.03717	0.08454	0.09167	0.06703	0.12026	0.06784	0.05133
Feb-04	0.03781	0.08511	0.0924	0.06803	0.12095	0.06801	0.05147
Mar-04	0.03843	0.08566	0.09312	0.06902	0.12162	0.06817	0.05162
Apr-04	0.03902	0.0862	0.09382	0.07001	0.12228	0.06831	0.05176
May-04	0.03958	0.08672	0.09451	0.07098	0.12291	0.06845	0.05191
Jun-04	0.0401	0.08722	0.09518	0.07195	0.12352	0.06857	0.05207
Jul-04	0.0406	0.08772	0.09584	0.07291	0.12411	0.06869	0.05222
Aug-04	0.04106	0.08821	0.09649	0.07385	0.12468	0.0688	0.05238
Sep-04	0.04149	0.08869	0.09713	0.07478	0.12523	0.06891	0.05254
Oct-04	0.04188	0.08917	0.09776	0.0757	0.12576	0.06902	0.0527
Nov-04	0.04224	0.08965	0.09839	0.07661	0.12627	0.06912	0.05286
Dec-04	0.04258	0.09013	0.09901	0.07751	0.12675	0.06923	0.05302
Jan-05	0.04289	0.09062	0.09962	0.07839	0.12721	0.06933	0.05318
Feb-05	0.04318	0.09111	0.10023	0.07926	0.12765	0.06945	0.05333
Mar-05	0.04345	0.09161	0.10084	0.08012	0.12807	0.06957	0.05348
Apr-05	0.0437	0.09212	0.10145	0.08096	0.12846	0.0697	0.05362
May-05	0.04395	0.09265	0.10206	0.08179	0.12883	0.06984	0.05376
Jun-05	0.0442	0.09318	0.10268	0.0826	0.12917	0.06999	0.05389
Jul-05	0.04445	0.09374	0.10329	0.0834	0.1295	0.07015	0.05402
Aug-05	0.04472	0.0943	0.10391	0.08418	0.1298	0.07033	0.05413
Sep-05	0.045	0.09489	0.10453	0.08495	0.13008	0.07052	0.05423
Oct-05	0.04531	0.09549	0.10516	0.08571	0.13034	0.07074	0.05433
Nov-05	0.04565	0.09612	0.10579	0.08645	0.13058	0.07097	0.05441
Dec-05	0.04602	0.09676	0.10643	0.08717	0.1308	0.07122	0.05448
Jan-06	0.04644	0.09743	0.10707	0.08788	0.131	0.07148	0.05454
Feb-06	0.04691	0.09812	0.10771	0.08858	0.13119	0.07177	0.05459
Mar-06	0.04743	0.09883	0.10836	0.08926	0.13136	0.07208	0.05463
Apr-06	0.048	0.09958	0.109	0.08992	0.13152	0.07242	0.05465
May-06	0.04863	0.10035	0.10964	0.09057	0.13168	0.07277	0.05467
Jun-06	0.04932	0.10116	0.11027	0.09121	0.13183	0.07314	0.05468
Jul-06	0.05006	0.102	0.1109	0.09183	0.13198	0.07354	0.05469
Aug-06	0.05086	0.10288	0.11151	0.09243	0.13213	0.07395	0.05469
Sep-06	0.05169	0.10379	0.11211	0.09303	0.13229	0.07439	0.05469
Oct-06	0.05257	0.10474	0.11268	0.09361	0.13246	0.07484	0.05469
Nov-06	0.05347	0.10572	0.11322	0.09417	0.13266	0.07531	0.0547
Dec-06	0.05439	0.10674	0.11373	0.09472	0.13288	0.07579	0.05472
Jan-07	0.05531	0.10777	0.11419	0.09526	0.13313	0.07629	0.05475
Feb-07	0.05621	0.10882	0.1146	0.09579	0.13343	0.07679	0.05481
Mar-07	0.05708	0.10985	0.11495	0.09631	0.13378	0.07731	0.0549
Apr-07	0.0579	0.11086	0.11523	0.09681	0.13419	0.07783	0.05503
May-07	0.05864	0.11179	0.11543	0.0973	0.13468	0.07835	0.0552
Jun-07	0.05929	0.11262	0.11553	0.09778	0.13525	0.07887	0.05543
Jul-07	0.05983	0.11329	0.11552	0.09826	0.13592	0.07938	0.05573
Aug-07	0.06024	0.11372	0.11538	0.09872	0.1367	0.07988	0.0561
Sep-07	0.0605	0.11382	0.11511	0.09917	0.13761	0.08037	0.05656
Oct-07	0.0606	0.11348	0.11468	0.09961	0.13867	0.08084	0.05713

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