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ABSTRACT

This paper analyses the role of information and communication technology (ICT) in Australia, Japan, South Korea and Taiwan within a framework of endogenous growth theory. The focus of this study is 'knowledge spillover' from ICT. The empirical results suggest that the knowledge spillover from ICT has a strong contribution to the economy-wide R&D; they also suggest that the contribution of ICT to output growth is very limited. These results are consistent with the recent finding that newly introduced technology involves a time lag to contribute to the output growth. As ICT is relatively a new technology, the effects of ICT seem to be still confined only in R&D activities.

Keywords: General; echnological Change: Choices and Consequences; Diffusion Processes; General; Information and Internet Services; Computer Software

JEL codes: O30 O33 O40 L86

CONTENTS

1. Introduction

The contribution of the information and communication technology (ICT) to economic growth has recently been investigated by a number of researchers. It is argued that its growth contribution depends on how ICT can induce broad-based economic growth (Stiroh, 2000, p. 9). Most ICT related studies focus on growth contribution from the *use* of ICT (i.e. growth effects of ICT capitals). A number of empirical studies, including Schreyer (2000), Pillat and Lee (2000), etc., find little support for such a broad-based growth contribution from ICT capitals. Furthermore, the evidence of ICT-led growth has been less supportive outside the USA. A recent OECD study points out that growth patterns of its member countries differ considerably, and suggests that the impacts of ICT are not uniform across the OECD countries (OECD 2001, ch.1). On the other hand, another group of studies focus on *knowledge* generated by ICT (i.e., growth effects of knowledge spillover from ICT). These latter studies highlight the relevance of ICT to 'knowledge economy'. The concept of knowledge economy is that sustainable economic growth can be achieved through expansion of knowledge-intensive industries, including ICT sector (OECD, 1996; Stiroh, 2001 and 2002). A series of studies by the OECD especially highlight that the ICT industries in most countries are heavily engaged in innovative activities— they are highly R&D intensive, and employ considerable number of skilled personnel (OECD, 2000 and, 2001, ch. III).

The above notion of knowledge-driven economic growth is analogous to that used in endogenous growth theories. Endogenous growth theories internalise technological progress. Endogenous growth theories consider technological knowledge from R&D activities as another form of input in production. It is argued that knowledge is not constrained by conventional resource constraint (Romer, 1990), and thus it induces increasing returns to scale in aggregate output production.

The present study aims at examining how the knowledge created from ICT sector contributes to technological progress in the economy as a whole. Following Porter and Stern (2000) and Furman *et al* (2002), we undertake the analysis by utilising patent statistics as the proxy measure of knowledge/innovations. Although it is well documented that patents are not an ideal measure of knowledge, patent statistics have an advantage of availability. Use of other proxies such as R&D expenditures has also its limitation especially in ICT sector. When considering Asian economies, it is almost impossible to obtain sectoral data on such proxies. Therefore, patent data is one of few possibilities to tackle the data limitation. This paper utilises the database developed by the National Bureau of Economic Research (NBER) on the basis of the US Patent and Trademark Office (USPTO) statistics. Unlike Porter and Stern (2000), we disaggregate patent statistics into its ICT and non-ICT components and then estimate knowledge production function. Our analysis focuses on Australia and three ICT-intensive Asian countries – Japan, South Korea, and Taiwan.

The structure of this paper is as follows. In section 2, we review the basic endogenous growth models with ICT knowledge spillover. Following the recent literature, this section also links ICT to the 'general purpose technology' (GPT) as the underlying motivation for our empirical analysis in the framework of endogenous growth models. Section 3 presents extended versions of 'idea-production' function as well as aggregate output production function, while section 4 deals with sources and compilation of data used for models estimation. We present empirical results in section 5, which is followed by the conclusion in section 6.

2. Endogenous growth theory with ICT knowledge spillover

Basic endogenous growth theories include Romer (1986, 1990), Lucas (1988), Grossman and Helpman (1991), Aghion and Howitt (1992), etc. Unlike the neoclassical growth theory, the endogenous growth theories internalise technological progress, which is considered to be vital for sustained economic growth. The endogenous growth theories recognise that R&D, which is primarily motivated by monopoly profit, is the central mechanism of technological progress.

Following Romer (1990), output production function (1) and knowledge production function (2) are as follows:

$$Y = H_Y{}^{\alpha} K^{1-\alpha-\beta} L^{\beta} A^{\alpha+\beta} \qquad (1)$$

$$\dot{A} = \delta H_A A \qquad (2)$$

where output (Y) is produced using physical capital (K) and unskilled labour (L). Also, the stock of economy-wide knowledge (A) in Romer's model enters into the output production function through the process for accumulation of new designs of intermediate durable goods. Knowledge production function (2) can be considered as R&D sector that develops the designs for the intermediates, which constitute physical capital (K). $\dot{A}$ is growth of knowledge (or technological progress), and δ is a productivity parameter. The economy allocates its skilled labour or human capital (H) into output sector (H_Y) and knowledge producing sector (H_A). It is to be noted that sustained output growth rate depends on knowledge producing sector's share of human capital (H_A).

As in (2), Romer assumes that knowledge production is the linear function of human capital devoted to R&D sector and the stock of knowledge. The linear assumption of knowledge production is based on non-rival and quasi non-excludable natures of knowledge. Under this assumption, the rate of technological progress depends on the share of human capital in R&D (H_A) and the R&D productivity parameter δ .

Jones (1995) extends Romer's model by removing the linear assumption of knowledge production function. In Jones model, knowledge stock is assumed to exhibit diminishing returns.

$$\dot{A} = \delta H^{\theta} A^{\phi} \tag{2b}$$

where $\phi < 1$ and $\varphi < 1$.

Jones's assumption is based on the fact that technological progress (measured by total factor productivity or number of patents) in many countries is not as fast as the growth of R&D personnel or R&D expenditures. Knowledge can, according to Jones, face diminishing returns because producing new knowledge increasingly becomes difficult as technological level increases.

Helpman and Trajtenberg (1992, 1994, and 1996) introduce the concept of 'general purpose technology' (GPT) as the fundamental technology that fosters R&D and innovations in wide range of industries. Helpman and Tradjenberg (1994, p.1) define the concept of GPT (e.g., semiconductor technology) as extremely pervasive and having not only the potential for continuous technological advances in the GPT itself; but also complementarities with manufacturing R&D. Information and communication technologies are the examples of adaptive innovations of semiconductor technology. While computer industry is identified as the early adaptor of semiconductor technology, communication industry is the late adaptor. In GPT literature, ICT has therefore been argued to have the characteristics of GPT.

In the framework of Helpman and Trajtenberg, a GPT is rather considered as a massive reap in technology (such as electricity), and not directly related to industrial R&D. However, the concept of technology that facilitates broad-based innovations (i.e. introduction of one technology induces wide range of innovations in many industries) provides useful insights to the present study. Because ICT is closely linked to a GPT, the present study focuses on how ICT knowledge facilitates broad-based innovations. We disaggregate an economy's overall knowledge stock (*A*) into ICT and non-ICT components, and analyse what extent the ICT-related knowledge contributes to broad-based technological change.

3. Empirical Framework

In this section, we utilise the empirical work by Porter and Stern (2000), and Furman *et al* (2002). Their 'idea-driven' model is the direct implementation of knowledge production function in Romer (1990). The notable points of Porter and Stern are direct focus on R&D (idea-production sector, in their expression) sector, and use of patent statistics as the measurement of knowledge. The studies by Porter and Stern and Furman *et al* directly focus on knowledge production function by using the patents as the proxy of innovations. The patent statistics, of course, is not ideal proxy of knowledge.

However, patent statistics, are widely available for many countries and for reasonable time length.

We extend the empirical model in Porter and Stern (2000) and Furman *et al* (2002) by distinguishing the ICT knowledge stock and non-ICT knowledge stock.[1] From R&D sector production function (2b), we have:

$$\ln \dot{A}_{it} = \delta + \theta \ln H_{it} + \phi \ln A_{it}$$

As same as before, $\dot{A}$ is the flow of innovation, or newly produced idea in country (i) and year (t). H is the level of R&D sector human capital, and A is the stock of knowledge from past innovations. By distinguishing ICT knowledge stock and non-ICT knowledge stock, we get:

$$\ln \dot{A}_{it} = \delta + \theta \ln H_{it} + \eta \ln AICT_{it} + \lambda \ln AN_{it} \qquad (3)$$

where $A_{it} = A_{it}(AICT_{it}, AN_{it})$, $AICT$ being the knowledge stock from ICT related innovations, and AN being the knowledge stock from non-ICT technological fields.

In our empirical analysis, we use HR as the number of researchers (a proxy of H), and PT as the number of total patents added in year (t) by the country (i). Similarly, the stock of ICT related patents ($ITPTS$) and the stock of non-ICT patents ($NPTS$) accumulated at time't' are the proxies of $AICT$ and AN respectively. The following is the specification of our knowledge production function to be used for estimation:

$$\ln PT_{it} = \alpha_i + \theta \ln HR_{it} + \eta \ln ITPTS_{it} + \lambda \ln NPTS_{it} + \varepsilon_{it} \qquad (4)$$

Note that dependent variable PT is a *flow* of patents while independent variables $ITPTS$ and $NPTS$ are *stocks* of patents. The productivity parameter (δ) is replaced by the country specific constant (α_i).

Note that, while estimating, we further include a dummy variable (YD) in the specification above. The value of the year dummy (YD) is equal to one for the year between 1998 and 1999, and zero for earlier observations. There are two reasons why we include this dummy variable. First, we try to capture the effects of currency crisis in East Asia in the late 1990s. Second, since the database only includes the patents that are already granted, not all patents applied in recent years appear in the database. In the case of the USPTO, the average time-lag between application and grant is usually around 2–3 years. Therefore, the number of patents applied after 1997 are likely to be fewer than the actual number. Although inclusion of outlying years can create a bias in our estimation, we do not remove the recent observations. This is because we are interested in ICT-related patents in particular, and we believe that inclusion of the latest observations is crucial in our analysis. Although problematic, because the number of patents appear on both sides of estimating equation (as the dependent variable, PT, and independent variables, $ITPTS$ and $NPTS$), the bias from lower number of patents for the recent years is not likely to be trivial.

In addition to the idea-production function (4), we also estimate an aggregate output production function. The output production (1) is similarly extended by disaggregating the economy-wide knowledge

[1] The model in Porter and Stern (2000, equation 7 & 8 on pp. 14-15) include dummy variables to control year and countries, as well as foreign patent stock variable. Furman *et al* (2002), on the other hand, consider various variables that indicate "innovative capacity".

stock (A) into ICT knowledge and non-ICT knowledge stock. The following is the specification of the output production function:

$$\log Y_{it} = \alpha + \beta \log K_{it} + \gamma \log L_{it} + \phi \log ITPTS_{it} + \lambda \log NPTS_{it} \quad (5)$$

Note that parameters are different from those in equation (1), as we do not impose any restriction on the parameters. The human capital variable (H_Y) is also removed since we do not have the precise measure of the human capital engaged in output production. We assume that the labour (*L*) comprises both skilled and unskilled labour, and that the effect of human capital is captured by *L*. In the knowledge production function, we do not consider any time lag. In other words, we assume that knowledge spillover occurs immediately when innovations take place. However, it is unrealistic to assume that newly patented innovations are produced immediately. In this section, we assume once-year lag between innovations and aggregate production. Thus, the equation above is modified to:

$$\log Y_{it} = \alpha + \beta \log K_{it} + \gamma \log L_{it} + \phi \log ITPTS_{it-1} + \lambda \log NPTS_{it-1} \quad (6)$$

4. Data

For empirical purpose, the present study will utilise the NBER patent database. The NBER provides the detailed dataset from the USPTO, and as mentioned above, the data is classified into 6 technological categories including computers & communications.[2] The USPTO patent statistics shows the countries of inventor, and covers most major Asian economies including South Korea and Taiwan. The database contains nearly 3 million patent data from 1963 to 1999. Each patent data includes the year of application and the year of grant. The present study uses the number of patents invented by Australia and three Asian countries - Japan, South Korea and Taiwan from 1981 to 1999. ICT related patents in our study corresponds to the NBER's category 'computers and communications'. Porter & Stern (2000) and Furman *et al* (2002) use 'the year of grant' to create patent statistics. We, instead, use the 'year of application' for the creation of patent statistics. This is because it is more reasonable to assume that the 'year of application' for a patent is a more appropriate measure of the timing of idea-production.

The knowledge stock is derived from the accumulative number of patents to the date. Depreciation of the knowledge needs to be considered. The basic model in Porter and Stern assumes no depreciation rates in patent stock.[3] On the other hand, Griliches (1990) suggests that the obsolescence of patents can be discrete.[4] In the present study, we arbitrarily set alternative depreciation rates: zero depreciation, discrete depreciation (assuming 15 years as the life of knowledge), and simple linear depreciation (5% and 10%). We have made several assumptions in deriving the initial level of patent stocks. For Japan and Australia, the database covers the patents (applied) from

[2] The technological fields are described in table (6). The detailed description of NBER dataset is provided in detail in Hall *et al* [2001].

[3] They also present the estimation using the knowledge stock with exponential depreciation rates.

[4] Griliches (1990) suggests that as renewing the patent protection is costly, renewing decision reflect the technical obsolescence of the particular patent. Those not renewed can be considered as obsolete technology. From this point of view, Griliches implies discrete depreciation of patents: zero depreciation during the patent life, and after that the depreciation jumps to 100%.

1945. Since there are only handful number of patents are applied until 1960s, we assume that the level of patent stock is zero prior to 1945. For Korea and Taiwan, application to the USPTO is not recorded until 1960s, and we have simply assumed that patent stocks are zero prior to first application.

As the NBER database only covers the US patents, it ignores domestic patents. The propensity to patent in the US may differ across three countries and may vary over the observed period. Thus, use of the USPTO statistics may suffer from propensity bias. However, as we do not have appropriate measure to amend this kind of propensity bias, we are compromised to assume that the propensity to patent in the US have been constant in all countries. The use of the US patent data, on the other hand, has various advantages. Using the US patent data can overcome the problems arise from institutional differences. As Archibugi (1992) points out, patent offices have different institutional characteristics, and each country has different legal system on patenting. The patents registered in the USPTO are examined by a single body with uniformed standard. This is a clear advantage for a panel analysis.

As the proxy for human capital engaged in R&D activities, the present study utilises the number of researchers in each country. As before, the numbers of researchers are from the OECD Science and Technology Database and from national statistics offices. GDP and capital are obtained from the World Bank's *World Development Indicators*. The level of employment, as the proxy for labour, is obtained from national statistics offices. Capital stocks are computed using the linear depreciation of 5%. The initial level of stock (K_0) is derived by:

$$K_o = \frac{I_0}{(g+d)}$$

Where I_0 is the level of investment in the initial year, and g is the average growth rate of investments. The term d is the depreciation rate, which is assumed to be 5%.

Graph-1 is the scatter diagram showing the relationship between R&D expenditures in ICT-related industries and the number of ICT-related patents (for Japan). There seems to be a strong linear relationship between R&D expenditures and the number of patents. This suggests that the number of patents is a good indicator of research activity.

Graph-2 shows four countries' proportions of ICT-related patents in total number of the USPTO patents. The proportions of ICT-related patents have been consistently rising in all four countries, very high especially in Japan and Korea. The proportion of ICT patents in Australia has been low reflecting low R&D intensity. On the other hand, the proportion of ICT patents in Taiwan has been low in spite of high R&D intensity in ICT industries. One of the possible explanations is the structure of ICT industries in Taiwan. Since Taiwan's ICT related production covers a wide range of computer components and peripherals (unlike Korea, which specialises in semiconductor industries), patenting activities seem to have been distributed over a variety of technologies.

Table-1 shows the mean values and the average growth rates of the variables for all the four countries. As the table indicates, the average growth rate of *PT* (the number of patents) is negative for Japan, suggesting that there seems to be slowing down of patenting activities in Japan. Strong contrast is South Korean case. As table-1 shows, the average growth rate of *PT* in South Korea has been the strongest among four countries, and this is especially due to a strong increase in its ICT-related patent stock.

5. Estimation Results

In this section, we present the results of the estimated knowledge production function (4). First, we show the estimation results of four-country panel (Australia, Japan, South Korea, and Taiwan). Then we present estimation results using a set of 4 three-country panel by removing one country from the original panel.[5] Similarly, we present the results of the output production function (6), using four-country panel and three-country panel.

Knowledge Production Function

We estimate the knowledge production function (4), using SUR method with fixed-effect. The table-2 shows the estimation results. Each column presents the estimation result with a particular depreciation rate of the patent stock. As seen in the table, all coefficients are positive and most of them are significant. *ITPTS* show higher coefficient values than *NPTS* except for 10% depreciation rate. As mentioned earlier, our primary interest is to find if the spillover from ICT related knowledge is stronger comparing to non-ICT knowledge. Our hypothesis is that coefficient for *ITPTS* is larger than *NPTS*. To test this hypothesis, we have conducted Wald coefficient test. Wald test rejects the null hypothesis of $\varphi = \lambda$ (i.e. coefficient for *ITPATS* is equal to *NPTS*) in favour of the alternative hypothesis of $\varphi > \lambda$ in two of four estimations. When zero-depreciation or discrete depreciation (with 15 years of patent life cycle) is applied Wald test rejects the null hypothesis, but fails to reject it when linear depreciation rates are applied to knowledge stock.

The analysis above is based on the four-country panel of Australia, Japan, South Korea, and Taiwan. In order to analyse each country more closely, we estimate the knowledge production function (4) using the three-country panel.[6] We remove one of the four countries from our panel and examine how it affects the estimation results. We therefore have four sets of estimation results in table-3. It is to be noted that the depreciation rate of the patent stocks is assumed zero in the table.

The first column of the table-3 shows the results from the panel consisting of Japan, Korea, and Taiwan. Exclusion of Australia increases the coefficients of both *ITPTS* (from 0.68 to 0.72) and *NPTS* (from 0.04 to 0.14), suggesting that Australia's knowledge spillover (both ICT and non-ICT) seems to be relatively weak. This is consistent with the level and the growth of R&D expenditures in Australia. Not only Australia is less R&D intensive, the ICT-related R&D in Australia has lower share than those in three Asian countries. The share of ICT in total business sector expenditures (BERD) in Australia is about 10% towards the end of 1990s, compared to 25% in Japan, 35% in Korea, and 50% in Taiwan.

[5] Using dummy variables can be an alternative method for capturing country-specific effects. However, we did not take this approach from the efficiency point of view. This is because inclusion of too many dummy regressors will certainly create a loss in degree of freedom.

[6] We did not estimate each country separately, as the number of observation is only 19.

The second column in table-3 is the panel estimation using Japan, Taiwan and Australia. Notably, the coefficient of *ITPTS* becomes negative when Korea is excluded from the panel. In contrast, the coefficient of *NPTS* rises sharply to 1.4. This finding indicates that Korea plays a significant role in ICT knowledge spillover. As mentioned above, the share of ICT-related research in Korea is as high as 35% of total BERD. Reflecting this, the average growth *of IPTS* in Korea (45%)[7] is highest among four countries. It is reasonable that exclusion of Korea from the panel has a massive impact on ICT knowledge spillover in this three-country panel analysis.

The third column in table-3 shows the estimation without Taiwan. As expected, the coefficient of *ITPTS* drops by 0.05. Exclusion of Taiwan, therefore, does not affect the ICT knowledge spillover as much as in the previous case (i.e. exclusion of South Korea). Although both South Korea and Taiwan both exhibit strong increase in ICT patents, as table-1 indicates, the growth of *ITPTS* in Taiwan is not strong (25%) as in South Korea (45%). The growth rate of *ITPTS* in Taiwan is about same as *NPTS* (23%). Unlike South Korea, where the growth of patents has been taken place predominantly in ICT, Taiwan demonstrates a balanced growth in *ITPTS* and *NPTS*. This may be the reason why the exclusion of Taiwan does not affect the balance between the ICT knowledge spillover and non-ICT knowledge spillover in three-country panel analysis.

The fourth column of table-3 corresponds to the estimation without Japan. Exclusion of Japan increases the coefficient of *ITPTS* by 0.07 and *NPTS* by 0.11. This may be the result of slower growth of both *ITPTS* and *NPTS* especially in recent years. As table-1 shows, Japan exhibits higher growth rates in *ITPTS* and *NPTS* than those in Australia, but much lower than South Korea and Taiwan. It also drops the panel coefficient value of human capital (*HR*) considerably to 0.05 from 0.07. This seems to be due to a very large number of researchers in Japan (although the growth rate is very low). As table-1 shows, the level of *HR* for Japan considerably dominates other three countries. This may be a reason why exclusion of Japan reduces the coefficient of *HR* dramatically.

Estimation Results of Output Production Function

The table-4 shows the results of the estimated output production function (6) using all four countries. As before, the estimations are undertaken with fixed-effect with SUR, and carried out with different depreciation rates. As seen in table-4, all the estimation results (with different depreciation rates) show that the coefficients for ICT patent stock are negative regardless of the depreciation rates. These results seem to suggest that the ICT knowledge stock may have negative effect on GDP growth. On the other hand, non-ICT patent stocks have positive coefficients, but the values are very small and insignificant in both estimations. The coefficient of labour is extremely large (it may be partly due to inclusion of skilled and unskilled labour in one variable), and the coefficient of capital has the values between 0.2 and 0.3. Wald coefficients test on the restriction of constant returns to scale (i.e. the null hypothesis of $\beta + \gamma = 1$) are rejected for all cases.

Our estimation results of output production function are consistent with phase-one effect of Helpman and Trajtenberg (1994, section 3.2).[8]

[7] See table (5).

[8] Helpman and Trajtenberg suggest that GPT fosters R&D to innovate new intermediates which accommodate the new GPT. However, the output production

When new technology (GPT) is introduced, it fosters R&D activity, but drags down the output production. This is because new GPT requires time to diffuse into output production. Newly introduced technology may, therefore, reduce output initially. While ICT patents have strong positive effects in knowledge production, these seem to have very limited effects on output production. ICT, therefore, seems to reflect one of the characteristics of GPT as Helpman and Trajtenberg have suggested.

As in the case of knowledge production function, we also estimate four output production functions of three-country panel by excluding one country in turn. Table -5 shows that exclusion of one country does not alter the general outcome obtained in four-country panel analysis. That is, the coefficient of *ITPTS* is negative and that of *NPTS* is positive in all cases. However, the fixed effects become positive when either Japan or Korea is excluded from the original panel. Exclusion of Japan or Korea also seems to affect the sizes of the coefficients: the coefficient value of *NPTS* rises, but the coefficient values of capital (*K*) and labour (*L*) drop sharply. These results may indicate that Japan and Korea have higher output elasticity with respect to capital and labour, and lower with respect to non-ICT knowledge.

The findings above also seem to be consistent with the argument in Jaffe and Trajtenberg (1994). As the R&D sector in Japan and Korea has high concentration of ICT, overall knowledge contribution (i.e., ICT and non-ICT combined) to GDP may have been low in these two countries. High output elasticity with resect to capital and labour in Japan and Korea may have been due to the limited knowledge-contribution. Exclusion of either Japan or Korea, therefore, reduces the coefficient values of capital and labour, and pushes up the coefficient of *NPTS*. Similarly, temporary drop in the economic growth (as a result of introducing ICT) can explain the changes in the signs of fixed effects. Thus, the high intensity of ICT in Japan and Korea may have been a force in slowing down their GDP growth rates to a larger extent than those of Australia or Taiwan.

initially drops as diffusion of new GPT takes time (phase one). When GPT is diffused into the output production (as new intermediates), the output growth begins to rise (phase two).

6. Conclusion

The paper has examined the knowledge spillover from ICT using the USPTO patent statistics. Our estimation results on *knowledge production function* show the evidence that knowledge from ICT sector seems to have higher spillover effects comparing to that of the non-ICT sector. This suggests that the knowledge created by ICT sector contributes more extensively, which, in turn, accelerates the aggregate R&D activities of the economy as a whole. On the other hand, our estimation results of *output production function* show that the ICT knowledge has limited impact on GDP growth. Our results are consistent with the phase-one effect of Helpman and Trajtenberg (1994 & 1996). They suggest that when an economy experiences a significant technological advancement (i.e., new GPT is introduced), R&D activities rise, but output production falls initially. This is exactly what we observe in our estimation results. The ICT knowledge seems to help accelerate the R&D activities, but it as such does not seem to contribute to the output growth in all the four countries we studied. Therefore, the contribution of ICT knowledge on GDP growth in these countries is yet to come.

7. **References**

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Table-1. Mean and average growth of variables

		PT	HR	ITPTS0	NPTS0	Y (Million)	K (Million)	L (1000)
AU	Mean	431	72814.81	334.625	7298.563	343000	1470000	7589.813
	Growth	-6.43%	4.25%	9.00%	5.94%	3.39%	2.30%	1.74%
JP	Mean	19524.38	570329.1	38811.25	220118.9	2580000	10200000	61987.79
	Growth	-4.26%	2.97%	12.45%	8.11%	2.78%	3.07%	0.82%
KR	Mean	916.0625	82096.94	977.75	3396.625	450000	1130000	17973.06
	Growth	25.28%	11.28%	45.81%	28.69%	7.41%	9.24%	2.10%
TW	Mean	1202.875	47054.38	475.875	6517.813	231000	342000	8346.438
	Growth	17.83%	10.18%	27.31%	23.08%	7.32%	7.54%	1.84%

Table-2. Estimations results of knowledge production function[9]

Dependent Variable: Log (PT)

Depreciation of patent	**Zero depreciation**		**5% depreciation**		**10% depreciation**		**15Year patent life**	
Variable	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
LOG(HR)	0.700	0.000	0.493	0.000	0.332	0.005	0.799	0.000
LOG(ITPTS)	0.686	0.000	0.493	0.000	0.398	0.000	0.622	0.000
LOG(NPTS)	0.047	0.737	0.358	0.004	0.512	0.000	0.067	0.639
Year Dummy	-1.373	0.000	-1.344	0.000	-1.237	0.000	-1.247	0.000
Fixed Effects								
Japan	-7.225		-6.014		-4.507		-8.046	
Korea	-6.047		-4.847		-3.532		-6.959	
Taiwan	-4.822		-4.005		-2.907		-5.693	
Australia	-6.229		-5.209		-3.909		-6.997	
R-squared	0.827		0.842		0.850		0.828	
Adj. R-squared	0.809		0.825		0.834		0.810	
Durbin-Watson	0.751		0.798		0.813		0.746	

[9] The values within the brackets are t-values. The variables are: HR = number of researchers; ITPTS = ICT sector patent stocks; NPTS = non-ICT patent stocks; YD = year dummy. The coefficients with *** are significant at 1% significance level, and similarly ** are significant at 5%, and * is at 10%.

Table-3. Estimation results from the knowledge production using three-country panels

Dependent Variable: Log (PT)

Countries included in the panel	**Japan, Korea, and Taiwan**		**Japan, Taiwan, and Australia**		**Japan, Korea, and Australia**		**Korea, Taiwan, and Australia**	
Variable	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
LOG(HR)	0.375	0.085	0.258	0.081	0.611	0.000	0.054	0.818
LOG(ITPTS)	0.724	0.000	-0.459	0.016	0.634	0.000	0.757	0.000
LOG(NPTS)	0.142	0.341	1.446	0.000	0.197	0.191	0.153	0.411
Year Dummy	-1.549	0.000	-0.939	0.000	-2.071	0.000	-1.211	0.000
Fixed Effects								
Japan	-4.462		-6.631		-7.272			
Korea	-3.302				-5.793		-0.023	
Taiwan	-2.347		-5.477				0.763	
Australia			-7.195		-6.197		-0.386	
Adj. R-squared	0.854		0.845		0.861		0.595	
Durbin-Watson stat	0.801		0.747		1.036		0.740	

Table-4. Estimation results from production function equation

Dependent Variable: Log (GDP)

Depreciation of patent	**Zero depreciation**		**5% depreciation**	
Variable	Coefficient	Prob.	Coefficient	Prob.
LOG(K)	0.193	0.003	0.326	0.000
LOG(L)	1.711	0.000	1.689	0.000
LOG(ITPTS)	-0.020	0.270	-0.011	0.506
LOG(NPTS)	0.091	0.001	0.032	0.142
Fixed Effects				
Japan	-8.802		-11.761	
Korea	-7.668		-10.605	
Taiwan	-6.895		-9.638	
Australia	-6.641		-9.544	
R-squared	0.998		0.997	
Adjusted R-squared	0.997		0.997	
Durbin-Watson stat	0.295		0.282	

Table-5. Estimation results from the output production function using three-country panels

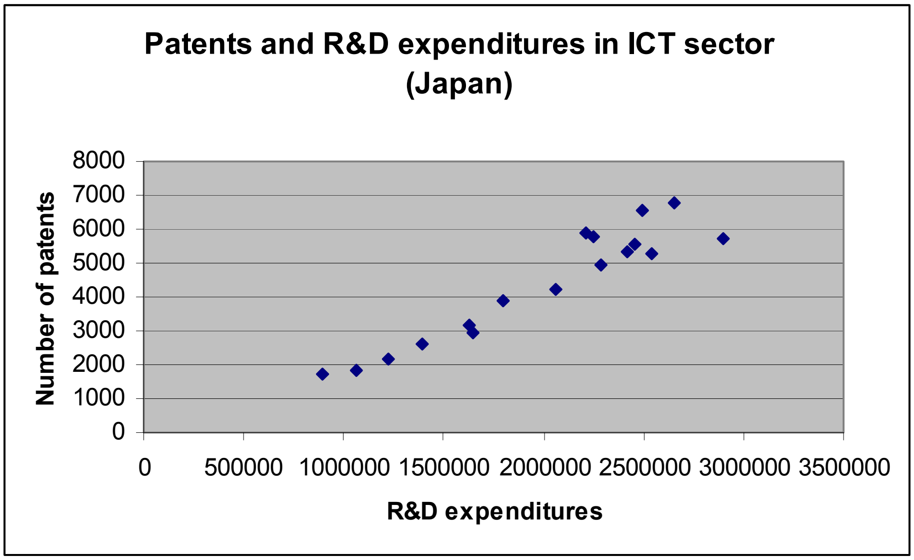
Dependent Variable: Log (GDP)

Countries included in the panel	**Japan, Korea, and Taiwan**		**Japan, Taiwan, and Australia**		**Japan, Korea, and Australia**		**Korea, Taiwan, and Australia**	
Variable	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Log (K)	0.117	0.261	0.000	0.993	0.335	0.001	-0.073	0.106
LOG(L)	1.741	0.000	1.043	0.000	1.677	0.000	0.628	0.000
LOG(ITPTS)	-0.045	0.055	-0.022	0.093	-0.016	0.555	-0.039	0.033
LOG(NPTS)	0.148	0.002	0.265	0.000	0.018	0.610	0.347	0.000
Fixed Effects								
Japan	-7.497		6.863		-11.609			
Korea	-6.337				-10.535		16.041	
Taiwan	-5.685		7.462				15.432	
Australia			7.823		-9.468		15.814	
Adjusted R-squared	0.998		0.999		0.998		0.966	
Durbin-Watson stat	0.261		0.542		0.596		0.158	

Table-6. The NBER database classification of the USPTO patents

Category number	Category name	The USPTO patent classes
1	Chemical	8 19 71 127 442 504106 118 401 42748 55 95 96 534 536 540 544 546 548 549 552 554 556 558 560 562 564 568 570 520 521 522 523 524 525 526 527 528 530 23 34 44 102 117 149 156 159 162 196 201 202 203 204 205 208 210 216 222 252 260 261 349 366 416 522 423 430 436 494 501 502 510 512 516 518 585 588
2	Computers and Communications	178 333 340 342 343 358 367 370 375 379 385 455431 380 382 395 700 701 702 704 705 706 707 708 709 710 712 713 714345 347360 365 369 711
3	Drugs & Medical	424 514128 600 601 602 604 606 607435 800351 433 623
4	Electrical & Electronic	174 200 327 329 330 331 332 334 335 336 337 338 392 439313 314 315 362 372 44573 324 356 374250 376 37860 136 290 310 318 320 322 323 361 363 388 429257 326 438 505191 218 219 307 346 348 377 381 386
5	Mechanical	65 82 83 125 141 142 144 173 209 221 225 226 234 241 242 264 271 407 408 409 414 425 451 49329 72 75 76 140 147 148 163 164 228 266 270 413 419 420 91 92 123 185 188 192 251 303 415 417 418 464 474 475 476 477352 353 355 359 396 399104 105 114 152 180 187 213 238 244 246 258 280 293 295 296 298 301 305 410 4407 16 42 49 51 74 81 86 89 100 124 157 184 193 194 198 212 227 235 239 254 267 291 294 384 400 402 406 411 453 454 470 482 483 492 508
6	Others	43 47 56 99 111 119 131 426 449 452 460 273 446 463 472 4732 12 24 26 28 36 38 57 66 68 69 79 87 112 139 223 45037 166 171 172 175 299 405 5074 5 30 70 132 182 211 256 297 312110 122 126 165 237 373 431 432138 277 285 40353 206 215 217 220 224 229 232 3831 14 15 27 33 40 52 54 59 62 63 84 101 108 109 116 134 135 137 150 160 168 169 177 181 186 190 199 231 236 245 248 249 269 276 278 279 281 283 289 292 300 368 404 412 428 434 441 462 503

Graph-1. Patents and R&D expenditures in ICT sector



Graph-2 Percentages of ICT-related patents in total number of patents