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# Knowledge Production Function in South Korea : An Empirical Analysis

## 우리나라 지식생산함수 : 실증분석

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목 차

## 국 문 요 약

본 연구는 공적분 패널방법론을 이용하여 우리나라 15개 산업의 지식생산함수를 추정하였다. 15개 산업의 지식생산함수간에 연관관계를 고려하여 Mark et al. (2005)가 제시한 동태적인 패널 공적분방법론인 DSUR을 이용함으로써, 기존의 방법론보다 효율적인 추정치를 제시하였다.

본 실증연구결과 및 정책적 시사점은 다음과 같다. 패널 공적분계수 추정치를 보면, 지식생산에 대한 연구자규모에 대한 탄력성은 0.25이며, 기존 지식축적량의 탄력성은 0.35로 추정되었다. 따라서 기존 지식축적량이 새로운 지식생산량에 기여하는 추정계수가 1보다 작음으로써, 장기적으로 경제성장은 물리적인 자원과 노동력 증대 그리고 정부의 역할에서 유인된다는 경제성장견해를 뒷받침하게 된다. 본 연구의 실증분석결과로 볼 때, 지식경제로 이행을 위한 정책시사점은 현재 정부주도적이고 직접적인 R&D정책추진구조에서 지식의 효율적인 창조 및 확산을 촉진할 수 있는 민간주도적이고, 간접적인 R&D정책구조로 전환이 요구된다.

핵심어 : 지식기반성장이론, 지식성장함수, 공적분계수, DSUR, R&D정책

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## ABSTRACT

In this paper we estimate knowledge production function for 15 South Korean industry sectors using panel data. To accommodate the influence of inter-sectoral interactions on the creation of knowledge, we estimate parameters for related knowledge production functions using the Dynamic Seemingly Unrelated Regression(DSUR) model proposed by Mark et al. (2005).

We find the elasticity of knowledge production with respect to the size of research staff to be 0.25 and that with respect to the existing stock of knowledge to be 0.35. The fact that the elasticity of new knowledge creation with regard to the existing knowledge stock is below 1 in South Korea corroborates the view that the rate of long-term growth of her economy is chiefly determined by the elasticity related to production functions of goods and services and the rate of population growth, and that her government policy, to ensure a continued growth for the Korean economy, must shift the focus of R&D policies from the current direct intervention-centered model to one consisting of indirect measures, namely supporting knowledge management and diffusion and the creation of a knowledge sharing system.

In terms of R&D policy implications it could be consider that the national knowledge production system should strengthen the cumulative process of knowledge accumulation and population for research and development. Our country R&D policy, also, need to adopt a global approach to increase knowledge stock at the highest levels of a country.

Key words : Knowledge-based economic growth, Knowledge production function, Cointegrated coefficient, DSUR, R&D policy

*JEL Classification* : O31, O41, F31

# I. Introduction

In most recent endogenous models of economic growth, macro production functions include knowledge stock or R&D stock. In the growth model proposed by Weitzman (1998), for example, the creation of new knowledge is effected through discovery of new combinations of existing knowledge, and this continuous creation of knowledge drives the continued expansion of the economy. In a similar vein, Jones (2005) argued that knowledge, by virtue of its being a non-competitive wealth, plays a capital role in the growth of an economy. Meanwhile, Caballero and Jaffe (1993), in their discussion of the importance of R&D in the production of knowledge, gives an in-depth treatment to the structural aspects of knowledge accumulation.1)

Weitzman (1996, 1998) pictured the creation of knowledge as a form of economy of scale realized from the existing stock of knowledge, while Jones (1995, 2002) and Kortum (1997) proposed growth models based on an assumed phenomenon of diminishing returns to scale. For Olsson (2000), knowledge production functions are a kind of concave functions with regard to knowledge opportunities. Existing knowledge opportunities, even if they continue to be used to produce new knowledge, may ultimately disappear completely, becoming an empty set. Hence, in knowledge-based growth models, the important issue is in less the simple role of knowledge accumulation in economic growth than the total economic contribution of the knowledge production function.

The estimation of the magnitude of the parameters of knowledge production functions has two mutually contradictory views on the prospects for long-term economic growth within endogenous growth theories. The underlying assumption of the endogenous models of economic growth developed by Romer (1990), Grossman et al. (1991) and Aghion et al. (1992), for instance, is that the contribution

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1) For searching a microfoundation of innovation theory, Klette and Kortum (2004) develop innovation model depending on Knowledge capital based on evidence on innovating firms.

of the existing stock of knowledge, as reusable elements, to the creation of new knowledge, keeps the scale of knowledge production constant. Endogenous growth models of this kind suppose the existence of a scale effect, whereby it is the size of R&D work force engaged in the production of knowledge that ultimately determines the rate of economic growth. Jones (1995) and Kortum (1997), on the other hand, propose weaker endogenous growth models, under which the production of knowledge is subject to diminishing returns to scale with regard to the aggregate stock of knowledge. Under this premise, the rate of increase in the size of R&D work force determines the rate of economic growth. In other words, the growth appreciates no scale effect and is chiefly determined by the rate of long-term population growth. In the case of Korean empirical test, Ha (2005) suggests that time series tests results support the trade off relationship between growth accelerating effects of increasing R&D intensity and growth decelerating effects of narrowing technological distance to frontier country.

Although there is little doubt as to the importance of knowledge production functions within growth theories, attempts to empirically measure them have been thus far few. This state of affairs has to do, on the one hand, with the insufficiency of available data, and with the absence of an adequate measurement method, on the other. In this study, we estimate knowledge production functions for 15 South Korean industry sectors using sectoral panel data from a period from 1982 to 2002. In acknowledgement of the fact that the creation of knowledge in an industry sector benefits from the existing stock of knowledge in other sectors, we estimate the parameters of knowledge production functions using the DSUR (Dynamic Seemingly Unrelated Regression) model proposed by Mark et al. (2005).[2]

Variables related to knowledge production functions estimated in this study are the number of patents registered, that of research workers and the surrogate variable for the size of knowledge stock, which is the cumulative number of patents registered since 1982. Treating these economic variables quantitatively

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[2] The importance of inter-sector interactions is acknowledged in most studies on the spillover of R&D, including by Griliches (1998).

requires a measurement technique capable of controlling nonstationary panel data. Kao et al. (2000) demonstrated that, when a cointegration relationship can be established in nonstationarypanel data, which is the case of the data in this study, the cointegrated coefficient can be estimated using one of the following three methods: OLS with bias-correction, FM-OLS (Fully Modified OLS) and DOLS (Dynamic OLS). However, this method proposed by Kao et al. tends to result in a low efficiency of parameter estimates, when there exist contemporaneous correlations between cross-sectional units of analysis. To sidestep this analytical issue, one can either resort to the SURE method proposed by Zeller (1962) based on the traditional panel estimation methodology or the technique proposed by Hsiao (1986), which consists in eliminating correlations existing between the units of analysis by adding or subtracting the mean value of cross-sectional units to or from the data. More recently, Mark et al. (2005) came up with a significantly more efficient estimator than existing methods for computing cointegrated coefficients: DSUR. In this study, we chose the DSUR estimator developed by Mark et al. (2005) for the estimation of knowledge production functions for South Korean industries.

The primary contributions of this study are as follows: First, by estimating knowledge production functions, hotly debated concept that is a central component of economic growth theories, using comparatively long-term data spanning a wide range of South Korean industry sectors, we offer a basis for selecting economic growth theories that are best adapted to the local knowledge economy environment. Second, the objective and optimal estimates of knowledge production functions provided by this study can assist policy making in R&D and forecasting of related policy effects.

The rest of this paper is organized as follows: in Section II, we describe in detail the importance of knowledge production function by presenting the economic significance of the parameters of knowledge production function within growth theories from recent years, and briefly present the measurement methods required to estimate the knowledge production functions that are relevant to this study. In Section III, we present the data used in the estimation and the results of the estimation. Finally, in Section 1V, we summarize the findings of this study and present implications for R&D policies, including policy priorities most likely to ensure continued economic growth.

## II. Estimation Methodology

### 1. Theoretical Background

In Jones' (1995, 2005) R&D-based growth model, knowledge production functions and related parameters are assigned the following roles in a country' s economic growth. For the sake of simplicity, let us say that the growth of a national economy is determined by its volume of labor and aggregate stock of knowledge. In other words,

$$Y_t = A^{\sigma} L_{Yt} \quad (1)$$

Here, let us assume that $\sigma > 0$. Labor, one of the factors of production, is distinguished into that for the production of goods and that for the production of knowledge, according to the following structures of determination:

$$L_t = L_0 e^{nt} \quad (2)$$

$$L_t = L_{Yt} + L_{At} \quad (3)$$

At any given point in time, knowledge output, another factor of production, is determined in the following manner:

$$\dot{A}_t = vL_{At}^{\lambda} A_t^{\phi} \quad (4)$$

Here, $v > 0$, and $\dot{A}$ corresponds to the newly-produced knowledge adding to the existing stock. $\phi$ is the parameters of the knowledge production function, the crucial elements in knowledge-based growth models. When a knowledge production function is conceived as in equation (4), the rate of increase in knowledge output can be determined in two different ways, depending on the magnitude of $\phi$. If $\phi < 1$, the rate of knowledge production increase will be determined as in the following:[3]

$$g_A = \frac{\lambda n}{1-\phi} \quad (5)$$

In equation (5)the rate of knowledge production growth is proportionate to that of population growth. Accordingly, the level of a country' s economic production or its level of production per capita is dependent on the population size of that economy. However, when $\phi = 1$, the knowledge production function in equation (4) may be given a simplified expression as below:

$$\dot{A}_t = vL_{At}^{\lambda} A_t \quad (6)$$

Equation (6) shows that the production of knowledge grows in function of $\lambda$, exponent of the size of R&D work force. Hence, economic growth of a country is determined by its size of population. In other words, growth rates in countries with larger populations are higher than in countries with smaller populations [scale effect].

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[3] See Jones (2005), pp. 1070-1072 for steps leading to equation (4).

The parameter with a decisive effect on growth, which is also the most important element in Jone' s R&D-based growth model, which assumes the size of $\phi$ is less than one, corresponding to the contribution of the existing stock of knowledge to the creation of new knowledge. Romer (1990), Grossman et al. (1991) and Aghion et al. (1992) developed their endogenous growth models on the assumption that $\phi = 1$. Jones' (1995) and Kortum' s (1997) models, on the other hand, assume that $\phi < 1$, which explains the more modest rate of growth under these models. Furthermore, the different sizes of $\phi$ call for different policy measures. If the parameter estimate of the knowledge production function in a sector is $\phi = 1$, this warrants aggressive policy measures to encourage R&D, it being an indication that economic growth may be accelerated through new creation of knowledge. If $\phi < 1$, this means that economic growth is rather determined by elasticities related to production functions of goods and services and long-term rate of population growth, making aggressive government policy in the R&D sector less pertinent [see Jones, 2005, p.1093].

In this study, we calculate the aggregate stock of knowledge using per-sector patent registration data for 15 South Korean industry sectors. Then, we compute the parameters of knowledge production function by estimating equation (4) using the measurement method described in the immediately following section of this paper, and derive implications for R&D policies from the results of this estimation.

One thing that must not be overlooked in the estimation of knowledge production functions for multiple industry sectors is the inter-sector transmission of knowledge. In other words the creation of new knowledge in any given sector benefits from knowledge spillover from other sectors, both directly and indirectly. Hence, for greater accuracy, one must acknowledge mutual influence between different industry sectors, rather than supposing the creation of new knowledge as an autonomous intra-sector process, and the estimation method must take into account the economic effect of the knowledge spillover.

## 2. Methodology

The method used in this study to estimate the parameters of knowledge production functions is the DSUR (Dynamic Seemingly Unrelated Regression) estimator proposed by Mark, et al. (2005). DSUR estimators resorting to simultaneous equations are widely considered more efficient than cointegrated vector estimators for panel data, when the residuals of functions are correlated. A cointegrated vector estimator for panel data proposed by Moon (1999) is quite similar to DSUR. However, DOLS-based SUR is known to be more efficient, when dealing with small samples, than the latter SUR estimator based on DOLS [Kao et al. 2000].[4]

As this study supposes the existence of an interlinkage between the 15 industry sectors studied, concerning the process of knowledge production, it is best to estimate related cointegrated coefficients using a system equation. DSUR is an optimal choice, because the samples used in this study match in terms of the number of sectors analyzed and years of time series data i.e. balanced data. We were able to confirm that Mark et al.' s DSUR estimator was substantially more efficient than simple DOLS, when each sample has a different coefficient, and the residuals of estimation equation are correlated.[5] We set up a knowledge production function as in the following and estimate related parameters using the DSUR estimator:

$$p_{it} = \alpha_i + \lambda_i l_{it} + \phi_i k_{it} + u_{it} \quad (7)$$

All lower-case symbols are log-transformed variables [ex: $k_{it} = \ln(K_{it})$]. Here, p is the number of registered patents for a given industry sector, l the number of

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[4] With large samples, the two estimators approach to identical number.

[5] Estimators by Kao et al, (2000) and Mark et al. (2003) are currently the two most popular estimators for empirical analysis of panel data.

research workers, k the size of the accumulated stock of knowledge, and u the residual term proposed by Saikkonen (1991), satisfying the assumptions needed for the estimation.[6] In this case, the DSUR estimator for the corresponding coefficient is as follows:

$$\begin{pmatrix} \hat{\beta}_{dsur} \\ \hat{\delta}_{p\_dsur} \end{pmatrix} = \left( \sum_{t=p+1}^{T-P} W_t \Omega_{uu} W_t' \right)^{-1} \left( \sum_{t=p+1}^{T-P} W_t \Omega_{uu} p_t \right) \quad (8)$$

In equation (8), $W_t = (X_t', Z_t')$, $X_t = (l_{it}', k_{it}')$, and $Z_t$ is the lead and lag variables of the two independent variables. $\Omega_{uu}$, the long-term cointegrated estimate and the most important estimate in the above estimation, is estimated in two separate steps [see Marke et al, 2005, pp.802-803]. The above DSUR estimator, specifically intended for cases where each of the samples has a different coefficient, enables the estimation of the coefficients using the information on the mutual interaction between the samples. The degree of the efficiency of the DSUR estimator varies depending on the degree of disparity between the coefficients. In this case, whether the coefficients are identical across the samples can be tested using the Wald statistic. The latter, estimated under the restriction that all coefficients are identical across all samples, has an asymptotic $\chi^2$ distribution, makes it possible to test the restrictive hypothesis at an appropriate level of statistical significance.

The advantages of the DSUR estimator expressed in equation (8) above, concerning this study, are as follows: First, the DSUR estimator is more efficient than other estimators, when estimating the parameters of knowledge production functions of industry sectors between which interaction exists in this area. Second, provided a sound parametric design, knowledge production functions can be more

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[6] For details on how related variables were selected and defined, refer to Section III.

accurately estimated through a parametric estimator than through a non-parametric estimator. Third and finally, the larger the variety of samples, the greater the consistency of DSUR estimates; in other words, parameter estimates converge faster to true parameter. In next section, we attempt to make the most of these methodological advantages of the DSUR model for our estimation of knowledge production functions for 15 South Korean industry sectors based on data from a period between 1982 and 2002.[7]

# Ⅲ. Empirical Results

## 1. Data

The data used in this study regard the number of patent applications and that of research workers in 15 industry sectors, over a 21-year period between 1982 and 2002. To convert the number of patents into the stock of knowledge of corresponding magnitude, we chose 1982 as the benchmark year and estimated the stock of knowledge capital of each of the 15 sectors for this year. The initial stock of knowledge capital was induced using equation (9) given below [see Hall, et al. 1995, p.270]:

$$K_{i0} = \frac{P_{i,1982}}{g_i^{av} + \delta_i} \quad (9)$$

Here, $K_{i,0}$ is the stock of knowledge capital in the year 1982 per industry sector, $P_{i,1982}$ the number of patent applications in 1982, and $g_i^{av}$ the average

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[7] The method, we use, is implicitly based on linear relation assumption. The other approach of nonlinearity is conducted by Cho, et al., (2003).

percentage change in the number of patent applications over the period 1982-2002, assuming the rate of increase in the accumulated stock of knowledge and number of patents remains constant. Finally, $\delta_i$ stands for the rate of depreciation for knowledge capital in each industry sector. The depreciation rate on knowledge capital was set to 5% in annual rate over a period of 20 years, corresponding to the patent term. After obtaining the size of the initial stock of knowledge capital, we estimated the total stock of knowledge capital for each of the years studied by adding the number of new patents, in other words, the new knowledge output for the year, to the depreciation rate and the size of accumulated stock at the outset, as in equation (10) below:

$$K_{it} = (1-\delta_i)K_{it-1} + P_{it} \quad (10)$$

The two graphs in (Figure 1) show the cross-sector trends in the aggregate stock of knowledge and number of research workers for 15 South Korean industries. The graphs indicate that both the number of research workers and size of the aggregate stock of knowledge increased steadily throughout the entire period studied, and that starting from the year 1990, the rate of increase in the stock of knowledge surpassed that in the number of research workers.[8] These visual observations, however, do not permit us to gauge the respective contributions of the size of research work force and the existing stock of knowledge. Therefore, in order to precisely measure the extents of their contributions, one needs to proceed to a quantitative estimation.

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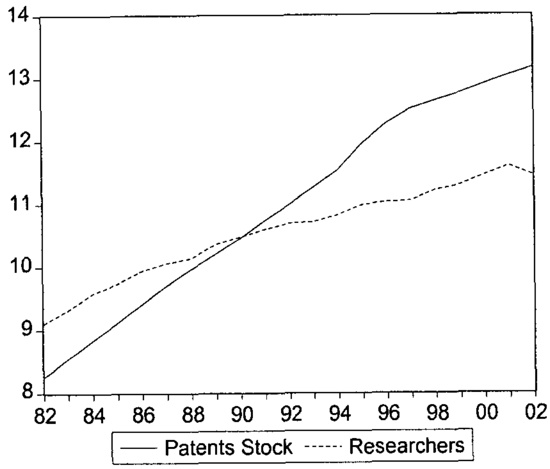
[8] The knowledge accumulation trend curve, when estimated through a simple regression equation, has a time-varying coefficient of 1.847 and is statistically significant.



(Figure 1) Trends in Accumulated Stock of Knowledge and Research Work Forces Since 1982

[Table 1] lists the knowledge stock and size of R&D work force in 15 industry sectors for the years 1982 and 2002.[9] The growth rate of knowledge accumulation in South Korea over the past 21 years is measured at 28% in annual average. The number of R&D workers rose at an annual average rate of 12% across all sectors, except the timber and wood product industry. A comparative examination of 15 industry sectors studied reveals that the chemical industry was the sector experiencing the highest accumulation of knowledge in 1982, and that this position was claimed in 2002 by the general machinery and equipment sector. The size of R& D work force was the largest in the chemical sector in 1982, and in 2002, ·in the electric and electronic industry. The compound annual growth rate (CAGR) of knowledge accumulation was the highest in the electric and electronic sector, measured at 37%. The precision machinery sector topped the list records a CAGR of 17% in the number of R&D workers.

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[9] One of referees indicates the relevance of patents to knowledge stock and suggests using total factor productivity in addition to patents. Recently Zachariadis (2003) show that using patenting or total factor productivity may be same results coming from empirical tests under U.S. economy.

[Table 1] Accumulated Knowledge Stock and Number of Research Workers by Industry Sector

| Sector | 1982 | | 2002 | | Average Rate of Increase(%) | |
|---|---|---|---|---|---|---|
| | Knowledge Stock | Size of R&D Work Force | Knowledge Stock | Size of R&D Work Force | Knowledge Stock | Size of R&D Work Force |
| Food, Beverages and Tobacco (1) | 607 | 749 | 843 | 2,436 | 15 | 6 |
| Textile, Apparel and Leather (2) | 67 | 519 | 155 | 1,086 | 19 | 4 |
| Timber and Wood Products (3) | 39 | 48 | 53 | 40 | 16 | -1 |
| Pulp, Paper, Print and Publishing (4) | 112 | 133 | 155 | 1,086 | 19 | 4 |
| Petroleum and Petrochemical Products (5) | 3 | 169 | 20 | 741 | 31 | 7 |
| Chemicals (6) | 1,000 | 1,375 | 1,505 | 10,326 | 19 | 10 |
| Rubber and Plastic Products (7) | 149 | 540 | 270 | 1,289 | 22 | 4 |
| Nonmetal Mineral Products (8) | 441 | 350 | 598 | 835 | 15 | 4 |
| Basic Metal Products (9) | 107 | 481 | 198 | 762 | 23 | 2 |
| Fabricated Metal Products (10) | 143 | 186 | 247 | 1,021 | 23 | 8 |
| General Machinery and Equipment (11) | 943 | 746 | 1,596 | 6,853 | 24 | 11 |
| Electric and Electronics (12) | 361 | 2,343 | 908 | 51,458 | 37 | 16 |
| Precision Machinery(13) | 200 | 84 | 419 | 2,443 | 32 | 17 |
| Transportation Equipment (14) | 90 | 1,208 | 174 | 13,440 | 28 | 12 |
| Furniture and Other Manufactured Goods (15) | 213 | 82 | 298 | 704 | 17 | 11 |
| Total | 3,852 | 9,013 | 6,876 | 93,906 | 26 | 11 |

## 2. Estimation Results

This study estimated knowledge production functions for 15 industry sectors in South Korea over a 21-year period between 1982 and 2002, using the parameter estimates explained in Chapter 2 of this paper. Before proceeding to the empirical analysis, we examined the correlations that may exist between industrial sectors studied, in the area of knowledge production.10) We used a simple DOLS estimator and estimated a knowledge production function via equation (7) for each of the 15 sectors. Next, using the coefficient estimates so obtained, we calculated residual terms for each sector and examined the correlations between the residual estimates. [Table 2] provides the coefficients of correlation between the 15 sectors studied. The coefficients of correlation were generally high between most sectors. These correlation data, reflected in the estimation of the parameters of knowledge production functions, can contribute toward the greater efficiency of the estimator. In other words, the degree of correlation existing between these 15 sectors suggests that they are best estimated through a simultaneous equation rather than through separate equations.

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10) Before one conducts the estimation of cointegrated coefficients, it is necessary to test whether each of the related variables are nonstationary. We used the panel unit root test procedure developed by Maddala and Wufor this purpose and found that the variables have unit roots. We did not include the results of the panel unit root test in this paper, as they have only modest pertinence to the main subject of this study. We also conduct the DSUR estimation in using the OECD country TFP data instead of industry patents and almost same results. This study results will be published in near future.

[Table 2] Inter-Sector Correlations in Knowledge Productions

| Industry Sector | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 0.2 | 0.5 | 0.6 | 0 | 0.1 | 0.4 | -0.1 | -0.2 | 0.2 | 0.3 | -0.1 | -0.2 | 0.4 | 0.2 |
| 2 | 0.2 | 1 | 0.1 | 0.1 | -0.2 | -0.2 | -0.1 | 0 | -0.2 | 0.1 | 0 | 0.2 | -0.3 | 0 | 0.5 |
| 3 | 0.5 | 0.1 | 1 | 0 | -0.1 | -0.3 | -0.1 | 0.2 | -0.2 | 0.4 | -0.1 | 0 | -0.1 | -0.1 | 0.4 |
| 4 | 0.6 | 0.1 | 0 | 1 | 0.1 | -0.2 | 0.4 | 0.1 | 0.2 | -0.2 | 0.6 | 0.1 | 0.4 | 0.5 | 0.1 |
| 5 | 0 | -0.2 | 0.1 | 0.1 | 1 | 0.2 | -0.2 | -0.2 | 0.7 | -0.2 | 0.3 | 0 | 0.4 | 0.5 | 0.2 |
| 6 | 0.1 | -0.2 | 0.3 | -0.2 | 0.2 | 1 | 0 | -0.6 | 0 | 0.2 | 0.1 | -0.2 | -0.6 | 0.1 | 0.1 |
| 7 | 0.4 | -0.1 | 0.1 | 0.4 | -0.2 | 0 | 1 | -0.2 | 0.1 | -0.1 | -0.3 | 0.1 | 0 | 0.2 | -0.2 |
| 8 | -0.1 | 0 | 0.2 | 0.1 | -0.2 | -0.6 | -0.2 | 1 | -0.1 | 0.2 | 0 | -0.3 | 0.2 | -0.1 | -0.2 |
| 9 | -0.2 | -0.2 | 0.2 | 0.2 | 0.7 | 0 | 0.1 | -0.1 | 1 | -0.1 | 0.2 | 0 | 0.5 | 0.5 | 0.2 |
| 10 | 0.2 | 0.1 | 0.4 | -0.2 | -0.2 | 0.2 | -0.1 | 0.2 | -0.1 | 1 | -0.1 | -0.2 | -0.3 | -0.1 | 0.4 |
| 11 | 0.3 | 0 | 0.1 | 0.6 | 0.3 | 0.1 | -0.3 | 0 | 0.2 | -0.1 | 1 | -0.3 | 0.1 | 0.4 | 0.1 |
| 12 | -0.1 | 0.1 | 0 | 0.1 | 0 | -0.2 | 0.1 | -0.3 | 0 | -0.2 | -0.3 | 1 | 0.4 | 0 | 0.4 |
| 13 | -0.2 | -0.3 | 0.1 | 0.4 | 0.4 | -0.6 | 0 | 0.2 | 0.5 | -0.3 | 0.1 | 0.4 | 1 | 0.3 | 0 |
| 14 | 0.4 | 0 | 0.1 | 0.5 | 0.5 | 0.1 | 0.2 | 0.1 | 0.5 | -0.1 | 0.4 | 0 | 0.3 | 1 | 0.1 |
| 15 | 0.2 | 0.5 | 0.4 | 0.1 | 0.2 | 0.1 | -0.2 | -0.2 | 0.2 | 0.4 | 0.1 | 0.4 | 0 | 0.1 | 1 |

The results of estimating knowledge production functions for South Korean industries are given in [Table 3]. The results of the DSUR estimation through a simultaneous equation, measuring the degree of contribution of the size of R&D work force to the creation of new knowledge, ranged from negative values to 1.55. The same range of variation was observed in the coefficients expressing the degree of contribution of the accumulated stock of knowledge. Next, we tested the hypothesis that the coefficients for the 15 industry sectors are identical and obtained results that reject the null hypothesis to the effect that the coefficients are identical.[11] Hence, the DSUR estimates of the knowledge production function for the overall Korean industry are 0.250 for the contribution of the size of R&D work force and 0.353 for that of the existing stock of knowledge.[12] This means that a 1% increase in the accumulated stock of knowledge is accompanied by a 0.35% increase in the creation of new knowledge.

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[11] The p-value is 0.00 and the null hypothesis to the effect that coefficient estimates are identical across all sectors is rejected.

[12] The coefficients related respectively to the R&D work force and the existing stock of knowledge, estimated under the assumption that coefficient estimates are identical across all sectors, were 0.39 and 0.74. When a time variable was included in the function, corresponding figures were 0.29 and 0.37.

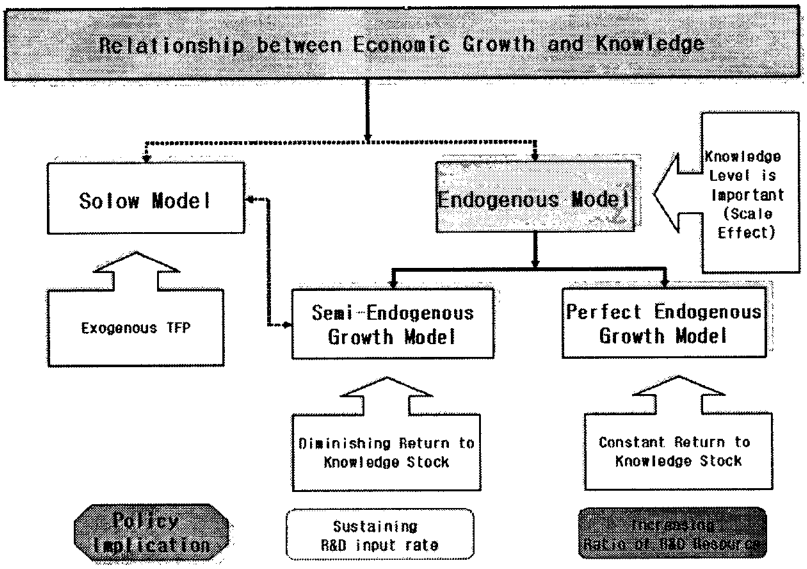
There has been practically no attempt to directly estimate knowledge production functions from the perspective of knowledge-based growth theories. However, the existing literature on the relationship between the accumulation of R&D capital and total factor productivity provides quite a few examples of studies reporting estimates that are very similar to ours. Griliches (1994), for example, estimated the degree of contribution of the stock of R&D capital to the growth of factor productivity at 0.30. The corresponding figure reported by Scherer (1982) is 0.29. The results reached by this study indicate that the degree of contribution of the size of R&D work force to the creation of new knowledge does not significantly differ from that of the existing stock of knowledge, reported by previous studies. However, this study is quite distinct from its predecessors, in terms of design of knowledge production function and factors of production, as well as at the level of estimation method. Hence, its relationship to existing studies maybe best described complementary.

[Table 3] Results of Estimating Knowledge Production Functions for 15 South Korean Industry Sectors

| Industry Sector | Contribution of R&D Work Force | Standard Error | Contribution of Accumulated Stock of Knowledge | Standard Error |
|---|---|---|---|---|
| 1 | 1.007 | 0.004 | -0.047 | 0.002 |
| 2 | -0.196 | 0.009 | 0.108 | 0.002 |
| 3 | -0.632 | 0.003 | -0.139 | 0.008 |
| 4 | -0.466 | 0.005 | 0.789 | 0.002 |
| 5 | 1.557 | 0.002 | -0.73 | 0.003 |
| 6 | 0.36 | 0.003 | -0.161 | 0.002 |
| 7 | -0.846 | 0.004 | 0.449 | 0.006 |
| 8 | -0.343 | 0.007 | 2.388 | 0.005 |
| 9 | 1.007 | 0.005 | 0.293 | 0.009 |
| 10 | 0.174 | 0.001 | 0.31 | 0.003 |
| 11 | -0.704 | 0.008 | 1.599 | 0.004 |
| 12 | -0.166 | 0.004 | 0.502 | 0.003 |
| 13 | -2.575 | 0.007 | 1.863 | 0.005 |
| 14 | -0.508 | 0.009 | 0.776 | 0.016 |
| 15 | 1.027 | 0.006 | 1.054 | 0.003 |
| DSUR Estimates | 0.250 | 0.0004 | 0.353 | 0.0001 |

The implications of the above estimation results are as follows: First, in South Korea, both the increase in the number of research workers and the existing stock of knowledge play an important role in the creation of new knowledge. Of the two factors of knowledge production, the accumulated stock of knowledge had a greater impact than the other. What this result suggests is that, in the case of South Korea, the creation of a knowledge management system to efficiently manage the existing stock of knowledge, to effectively facilitate the diffusion and to broadly share knowledge assets is of paramount importance for the creation of new knowledge. Second, $\phi$ for South Korea was less than 1, which is the threshold value in R&D-based growth theories. This result lends the positive evidence for the existing view that in Korea, the rate of economic growth is determined mainly by elasticity related to production functions of goods and services and the rate of population growth, and that, for this reason, the government must shift the focus in its R&D policy from a direct intervention-centered model to one involving indirect measures to facilitate the management and diffusion of knowledge and the creation of an effective knowledge sharing system. The result also suggests that the weaker endogenous growth models like the ones proposed by Jones (1995) and Kortum (1997) which suppose $\phi < 1$ are more adapted to Korean economic reality than those others developed by Romer (1990), Grossman et al. (1991) and Aghion et al. (1992) which suppose $\phi = 1$. Finally, we calculate the degree of contribution of the existing stock of knowledge needed for South Korea to achieve a growth rate of 5%, frequently quoted as the optimal rate of economic growth. Given the estimate of the contribution of the size of R&D work force at 0.250 and assuming a 1.5% labor force growth rate, the rate of contribution by the existing stock of knowledge in order to achieve a 5% economic growth must be 0.75 at the very least. This is more than the double the current rate of contribution by the accumulated stock of knowledge in South Korea. It is not impossible to attain this high level of elasticity of production of new knowledge with regard to the accumulated stock of knowledge, provided an efficient system for managing R&D is in place.

Recently Ha et al. (2007) try to find out the existence of empirical difference between the semi-endogenous growth model and fully endogenous growth model in using knowledge production function approach. Important differences between our empirical results and their results are that first, our finding supports the semi-endogenous growth theory. Second, our empirical results are derived from more powerful panel analysis. Our empirical findings for two important parameters in knowledge production function will give light on such future study efforts and suggest the relevant R&D policy implications in Korea. For concrete study implication, we visualize the different policy implications according to different growth models in (Figure 2).[13] As indicated in (Figure 2), our empirical results suggest that our country R&D policy be on semi-Endogenous growth model's prediction. There is no very wide rage of R&D intervention policy working in that point.



(Figure 2) R&D policy implications in three different growth models

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[13] We visualize the main results in modifying Ha et al. (2007) study results.

# IV. Conclusion and Implications

The goal of this study is to estimate knowledge production functions, which is the one of the most important elements constituting theories of endogenous economic growth that emerged in the recent decade by using the most efficient estimator. Having chosen the DSUR estimator proposed by Market al. (2005), we analyzed long-term data for the period 1982-2002, from 15 South Korean industry sectors, to empirically estimate the extent of contribution of the accumulated knowledge stock and the size of R&D labor force to creating new knowledge. Our results indicate that a 1% increase in the number of R&D workers would contributes a 0.25% growth in new knowledge, and a 1% increase in the size of the accumulated knowledge stock, a 0.353% growth.14)

This study has the important theoretical and policy implications. It contributes to the study of endogenous economic growth theories by providing empirical support to related semi-endogenous growth models proposed by Jones (2005) and Kortum (1997). Meanwhile, for policy makers, we demonstrate through concrete evidence that, to ensure the continued growth of the South Korean economy, the government policy in R&D must assign greater importance to infrastructure for diffusing and sharing knowledge than direct support toward research projects.

Selecting appropriate variables optimally capturing the state of knowledge and developing a measurement method which can improve accuracy and mitigate the sensitivity of parameter estimates would be two of the most important tasks for future research. Also, for greater rigor in the estimation of knowledge production functions, the scope of research must be continuously broadened, by including either more diverse industry sectors or countries, to expand the body of knowledge in this research field.

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14) Because of each industry market structure problems, one of referees indicates the empirical results need to be interpreted carefully. For controling market structure problem issues, refer to Yoo, (2003).

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**조상섭**

한양대학교 경제학석사, University of Missouri at Kansas City에서 회계학석사 그리고 Saint Louis University에서 "A Cointegrated Panel Analysis and the Convergence Hypothesis"로 경제학박사학위를 취득하고 현재 호서대학교 디지털비즈니스학부 전임교수로 있으며, 주요 관심분야는 국가간 산업간 성장에 R&D역할 및 관련 실증분석과 정보통신산업관련 분야를 연구하고 있다.

**정동진**

고려 대학교에서 경제학박사학위를 취득하고 현재 정보통신연구진흥원에서 기술정책연구팀장을 역임하고 있으며, 거시적 IT산업분석과 국가 R&D성과분석 그리고 기업 및 국가수출행위분석에 대한 연구를 수행하고 있다.