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기술혁신이 생산성과 경제성장에 미치는 영향*

The Contribution of Innovation on Productivity and Growth in Korea

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목 차

국 문 요 약

기술혁신이 경제성장에 미치는 영향은 어떠한가? 이는 전통적으로 지식스톡을 반영하는 성장회계법에 의해 분석되었다. R&D에 대한 수익률 추정은 특허와 같은 R&D 산출이 지식축적에서 기인하는 것으로 파악한다. Griliches(1973)는 이를 위해 회귀분석 방법을 사용하였다.

본 연구에서는 기존 성장회계법에서의 추정방법과 달리 R&D 효율성을 나타내는 파라미터가 시간이 지남에 따라 변동(time-varying)하는 것을 허용하는 상태공간 모형(state-space model)을 통해 한국경제의 R&D효율성(fertility)을 추정하였다. R&D스톡의 생산성에 대한 탄력성은 0.120~0.135 정도로 추정되었다.

핵심어 : R&D, 총요소생산성, 기술혁신, R&D 수익률

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ABSTRACT

What has been the contribution of industrial innovation to economic growth? Typically, the issue has been approached with growth-accounting methods augmented to include a "stock of knowledge". An independent estimate of the rate of return to R&D is found in order to impute patents granted to the accumulation of knowledge. Griliches(1973) then uses a regression approach to assess the effect of an R&D variable on the computed TFP growth rate. The regression coefficient on the R&D variable would provide an estimate of the social rate of return to R&D. The related studies tend to show high social rates of return to R&D, typically in a range of 20 to 40 % per year.

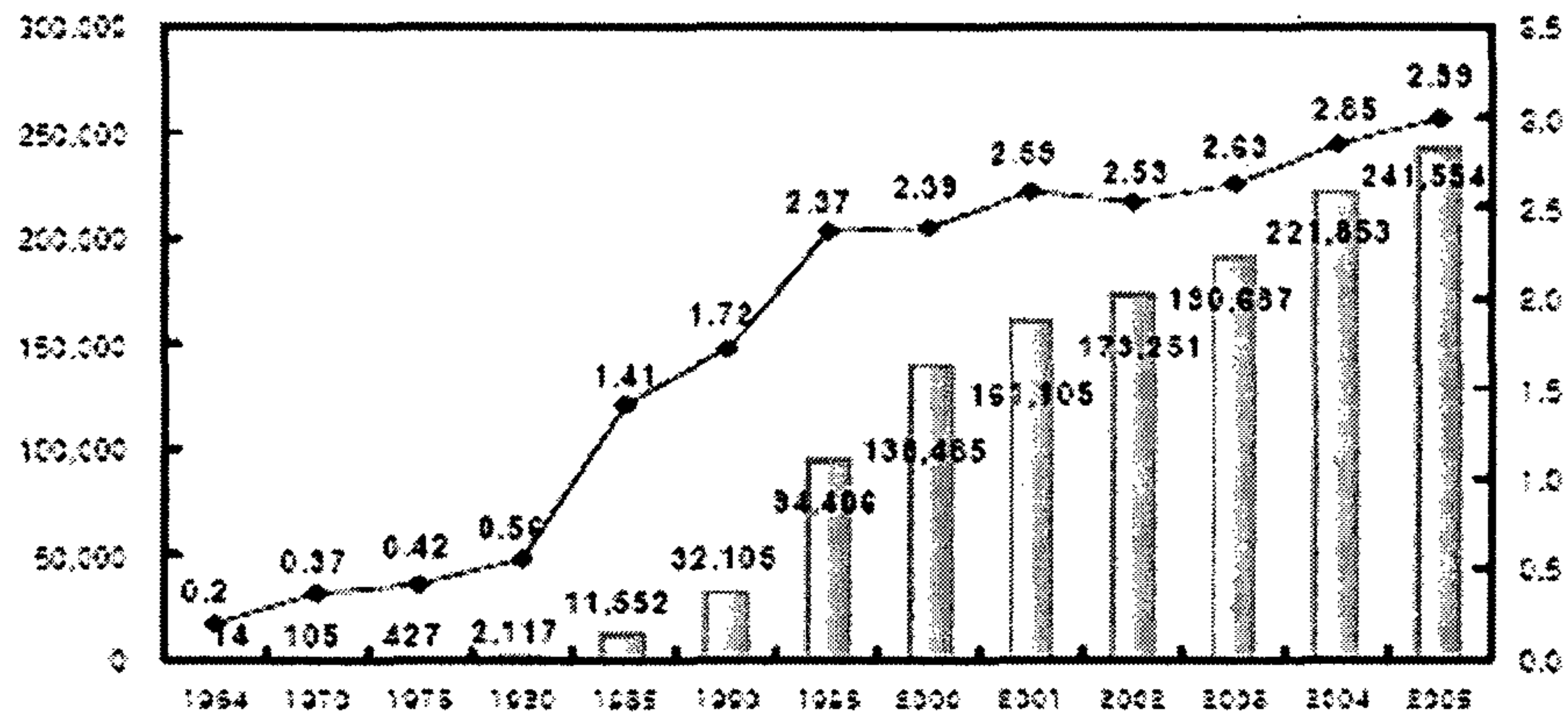
We need to provide multiple equation dynamic system for productivity and innovation in Korean economy in state space form. A wide range of time series models, including the classical linear regression model, can be written and estimated as special cases of a state space specification. State space models have been applied in the econometrics literature to model unobserved variables like productivity. Estimation produces the following results. Considering the goodness of fit, we can see that the evidence is strongly in favor of the range 0.120~0.135 for the elasticity of TFP to R&D stock in the period between 1970's and the early 2000's.

Key Words: R&D, TFP(total factor productivity), industrial innovation, rate of return to R&D.

Ⅰ. Introduction

Since the early 1960s, several East Asian countries including South Korea have grown at an unprecedented rate, especially the four "dragons". The contribution made to this growth by improvements in TFP has been examined by Young(1995) in an influential paper.

Not only has spending on research in Korea been growing in real terms, but its relative importance compared to other economic activities has been steadily increasing as well in Korea. (Figure 1) depicts the trends in the ratio of R&D to value added in industry in the Korean economies.



(Figure 1) National Trend in R&D of Korea (Source: MOST)
[Line: percentage of GDP(%), Bar: Total R&D expenditure(100 million Won)]

It was Solow(1956) who formalized the idea that capital deepening could cause labor productivity to rise in a dynamic process of investment and growth. The model's critical assumption concerning the product function is that it has CRS(constant returns to scale) in its two arguments, capital and labor. In addition, intangibles such as human capital and knowledge capital have peculiar economic properties that may not be well represented by the standard formulations. In the mid-1980s it became increasingly clear that neoclassical growth model was theoretically unsatisfactory. The model predicts that, without technological change, the economy will eventually converge to a steady state with zero per capita growth. These problems motivated researchers to introduce some aspects of imperfect competition to construct satisfactory models in which the level of the technology can be advanced by purposeful activity, such as R&D expenditures. Models of this type were pioneered by Romer(1990) and Aghion and Howitt(1992).

Meanwhile, what has been the contribution of industrial innovation to economic growth? Typically, the issue has been approached with growth-accounting methods augmented to include a "stock of knowledge". Of course one cannot directly observe the reward paid to the knowledge stock as most of the returns are hidden in data on corporate profits. So an independent estimate of the rate of return to R&D is found in order to impute output expansion to the accumulation of knowledge. The rate of return on R&D has been estimated econometrically using cross-sectional data on firms or industries, by invoking the assumption that units in the sample share a common rate of return.

In this paper, we review endogeneous growth models of intentional industrial innovation that suggest a possible way to extend the usual growth-accounting procedure to assess the contribution from R&D.

II. Basic Growth Accounting Method

1. Backgrounds: Economic Growth Model

It was Solow(1956) who formalized the idea that capital deepening could cause labor productivity to rise in a dynamic process of investment and growth. The view that innovation is driven by basic research, which is implicit in the models with exogeneous technology, was made explicit in a paper by Shell(1967)(Aghion and Howitt, 1998).

Now we let the productivity of labor depend upon the economywide cumulative experience in the investment activity, that is, on the aggregate stock of capital. Then aggregate output of Z will be given by $Z=F[K, A(K)L]$.

The first argument in F( ) represents the private input of capital by all firms in the economy. The second argument reflects their aggregate employment of effective labor, which depends in part upon the state of technology, as represented by the term A(K).

Romer(1986) provides an alternative interpretation of this specification. He views K itself as knowledge. Knowledge is created via an R&D process. Firms invest in private knowledge, but at the same time they contribute inadvertently to a public pool of knowledge, which is represented here by A(K). The basic idea of Frankel(1962)' s AK model was rediscovered Romer (1986), who cast his analysis in terms of the Ramsey model of intertemporal utility max. by a representative individual, taking into account that individuals do not internalize the externalities associated with the growth of knowledge.

2. Previous Literature Review and Basic Model

In 1957, Solow published "Technical change and the aggregate production function". In the article, he performed a simple accounting to break down growth in output into growth in capital, labor and technological progress. Solow, in addition to economists such as Denison(1962) and Jorgenson(1967) who followed Solow' s approach, used the key formula of growth accounting to know the sources of growth in output.

While results from these studies vary, most investigators find private rates of return in excess of thirty percent (Griliches 1973; Mansfield et al. 1977; Scherer 1982). Based on a return of 30 percent, Griliches(1973) estimates that R&D contributed perhaps 0.3 percent to measured productivity growth in 1966 and 0.2 percent in 1970 in the US.[1] An extensive analysis of productivity levels using

1) The R&D program summarized by Griliches(1973) focuses on R&D spending as a determinant of the TFP growth. Earlier contributors to this literature include Terleckyj(1958), Minasian(1962), Griliches(1964) and Mansfiels(1965). The empirical methodology described by Griliches(1973) accords well with the general setting of the product varieties model. The Griliches approach begins by applying the usual growth accounting analysis to compute a residual.

growth accounting can be found in Klenow and Rodriguez-Clare(1997) and Hall and Jones(1999). They noted that the fit of the model could be improved more by extending the model to include human capital. The US Bureau of Labor Statistics(BLS) provides a detailed accounting of US growth. Among an average annual rate of 2.5% between 1948 and 1998 in output growth, TFP accounts for 1.4% points.

Growth accounting is often viewed as a first step in explaining the TFP growth rate as estimated in equation as follows.

$$Y= F(A,\ K,\ L) = Ae^{\lambda t}\ K^{\alpha}L^{(1-\alpha)}T^{\beta} \qquad (1)$$

where A is the level of technology, λ is growth parameter, K is the capital stock, T is the technological knowledge stock and L is the quantity of labor. The growth rate of output can be partitioned into components associated with factor accumulation and technological progress. Taking log of equation (1) and derivatives with respect to time we get

$$(\Delta Y/Y) = \lambda + \alpha(\Delta K/K) + (1-\alpha)(\Delta L/L) + \beta(\Delta T/T) \quad (2)$$

Equation (2) says that the growth rate of GDP can be decomposed into the growth rate of the three inputs: capital, labor and knowledge stock.

Specifically, the contribution of technological progress to growth can be calculated from equation (2) as a "residual"or difference between the actual growth rate of GDP and the part of growth rate that can be "accounted for" by the growth rate of capital and labor:

$$(\Delta A/A) = (\Delta Y/Y) - \alpha(\Delta K/K) - (1-\alpha)(\Delta L/L) \qquad (3)$$

Equation (2) is valid when A and L are changing as long as the marginal products of labor and capital are equated to their factor prices. Therefore, the usual approach for computing the TFP growth rate yields, in this model,

$$(\Delta A/A) = \lambda + \beta(\Delta T/T) \tag{4}$$

Note from equation (4) that the endogeneous-growth part of Solow residual reflects only the fraction β of the growth rate of knowledge stock.

In the basic model of the endogeneous growth model, R&D stock is proportional to the amount of output devoted to R&D, that is, $\Delta T = (1/\eta)(R\&D)$, where η is the amount of R&D required to achieve a unit increase in T. The measured TFP growth rate in equation (3) therefore satisfies

$$(\Delta A/A) = \lambda + \rho(\Delta T/Y) \tag{5}$$

$$(\Delta A/A) = \lambda + \rho\ (R\&D/Y) + \varepsilon \tag{6}$$

where ρ is the rate of return to R&D, ε is disturbance term, and R&D is the R&D flow.

The empirical methodology described in Griliches(1973) accords with the general setting of the above growth model. The Griliches approach begins by applying the usual growth-accounting analysis to compute a residual. This method corresponds to the calculation of $(\Delta A/A)$ in accordance with equation (3). Griliches then uses a regression approach to assess the effect of an R&D variable on the computed TFP growth rate. For example, the TFP growth tate could be regressed on R&D expenditures (typically expressed as a ratio to output or sales), a trend term (to pick up exogeneous technical progress) and random influences. The regression coefficient on th R&D variable would provide an estimate of the social rate of return to R&D. The studies tend to show high social rates of return to R&D, typically in a range of 20 to 40 % per year in the US economy.

The empirical literature distinguishes between the private return and the social return to R&D. The former refers to the estimate of ρ using a firm' s own R&D share as the explanatory variable. The latter attempts to mitigate measurement problems and to capture interfirm technology spillovers by focusing on the industry level. ⟨Table 1⟩ provides a partial review of estimates of so-defined "social"rates of return from the productivity literature. Estimates of the social return average about

28% when only R&D from one' s own industry is included and average nearly 100% when the broadest concept of return (the sum of the two columns in the table) is employed.[2)]

〈Table 1〉 Estimated Rates of Return to R&D[3)] [( ): standard error]

Study	ρ (own)	ρ (used)	Sum
Sveikauskas(1981)	0.17(.06)		
Hall(1995)	0.33(.07)		
Griliches and Lichtenberg(1984b)	0.34(.04)		
Terleckyj(1980)	0.25(.08)	0.82(.21)	1.07
Sherer(1982)	0.29(.14)	0.74(.39)	1.03
Griliches and Lichtenberg(1984a)	0.30(.09)	0.41(.20)	0.71

Kwon(2003) finds that through estimating the rate for manufacturing sector in Korea, the return to R&D is somewhat higher than that of developed countries. He estimated the return as 26-33%. Shin(2005) used CES production function for analyzing the spillover effects of R&D on technological progress in Korea. If it is assumed that technical progress is Hicks neutral, the elasticity of R&D stock on TFP is 0.252. These models all assume that the parameter for denoting R&D efficiency is time-invariant. But, in this paper, we relax this assumption and apply time-varying estimation method using state-space method.

Ⅲ. Results from the Estimation Model

The data set consists of some macro-economic variables like rate of GDP, physical capital stock, magnitude of labor, GDP, R&D investments etc. observed for

2) Griliches(1991) reviews literatures that seek to estimate the social rate of return to R&D, and finds social rates of return on the order of 40 to 60%, far exceeding private rates of return.

3) Jones and Williams(1997).

35 years(1970-2004) in the Korean economy. They were obtained from BOK, KOSIS, OECD and IFS.

1. Estimation of the rate of return to R&D: OLS

We examine a simple model of the growth rate of productivity for technical innovation represented by proxy variable, total R&D expenditures: In a steady-state the growth rate of output is equal to the growth rate of A. In this section, the rate of growth in TFP is regressed on the amount of output devoted to total R&D (ΔT) divided by GDP in equation (5).[4)]

OLS regression produces the following results in ⟨Table 2⟩.[5)] Estimated standard errors are given together. Significantly estimated rate of return to R&D is 17.6%.

⟨Table 2⟩ Estimation Results for the Rate of Return to Total and Public R&D(Flow)[6)7)]

Variable	Coefficient	t-Statistic	Prob.
Constant	-0.031	-4.815	0.000
RD/GDP	0.176	4.055	0.0003*
Constant	-0.018	-1.758	0.092
GRD/GDP	0.438	1.817	0.0824**

4) Generally, the literature distinguishes between the private return of R&D and the social return of R&D. The latter mitigates measurement problems and capture spillovers by focusing on the industry-level data. In this paper, if innovations are used in the same industry, data aggregation to the whole economy level mitigates these problems. But, the omission of measurement of R&D efficiency of used inputs may be the main limit of this paper. Previous study shows that, when the broadest concept of return is employed in Korea, estimates of the (social) elasticity average about 32(%)[=14(own)+18(used)].(Kim and Lee, 2003) See ⟨Appendix⟩.

5) Though R that is a measure of the fit of the OLS model is somewhat low such as 0.33 and 0.13, we show the estimation result for comparing state space estimation results.

6) If estimated coefficient is statistically significant, we denote * and **, by 5%, 10% significance level, respectively.

7) In ⟨Table 2⟩, the measures of goodness-of-fit, R^2 is derived relatively low as 0.333 and 0.125, respectively. In the first case, 33.3% of variation of productivity growth is explained by the variation in R&D intensity. Th reason is that total variation of productivity growth is not explained only by R&D intensity. It is affected also by the change in social infrastructure, government policy, and so on.

We also examine a simple model of the growth rate of productivity for public technical innovation represented by government R&D expenditures: the rate of growth in TFP is regressed on the amount of output devoted to public R&D(ΔT: GRD) devided by GDP in equation (5).

OLS regression produces the following results in ⟨Table 2⟩. Significantly estimated rate of return to public R&D is 43.8%.

2. Time-varying Random Coefficients Model: R&D Flow

We need to provide multiple equation dynamic system for productivity and innovation in state space form. A wide range of time series models, including the classical linear regression model and ARIMA models, can be written and estimated as special cases of a state space specification. State space models have been applied in the econometrics literature to model unobserved variables: expectations, measurement errors, missing observation, permanent income, unobserved components, natural rate of unemployment, and TFP.

There are two main benefits to representing a dynamic system in state space form. First, it allows unobserved variables(state variables; productivity, knowledge level) to be incorporated into, and estimated along with, the observed model. Second, it can be analyzed using a powerful recursive algorithm known as Kalman filter. The Kalman filter algorithm has been used, among other things, to compute exact, finite sample forecasts for Markov switching models and time varying (random) coefficient models. State space models have a wide range of potential applications in econometrics, since economic growth theory often involves unobservable variables - for example, R&D fertility(efficiency).[8)]

Generally, the model $yt = Xt\beta + \varepsilon t$ is analyzed within the frameworks of constant coefficients. It does have the assumption that there is no parameter variation across times. It derives only one value across periods for R&D efficiency.

8) Nowadays, DOLS and FMOLS are mainly used for panel data at firm-level data. But, state space model have great advantage in making inference for time-varying parameter.

A fully general approach would combine all the machinery of the traditional models with a model that allows β to vary across times. The main difference of this paper from others lies in this point.

Parameter heterogeneity across times can be modeled as stochastic variation. Suppose that we write[9)]

$y_t = \beta_t x_t + \varepsilon_t$

where

$\beta_t = \beta_{t-1} + u_t, \qquad u_t \sim N(0, \sigma 2)$

We examined a simple model of the productivity for technical innovation represented by proxy variable, R&D:

$\log A_t = c(1) + SV_t \log T_t + \varepsilon_t$

$SV_t = SV_{t-1} + u_t, \qquad u_t \sim N(0, e^{c(2)})$[10)]

T_t: R&D investment flow

Estimation (considering autocorrelation of parameter) produces the following results in 〈Table 3〉. Estimated standard errors are given together. Considering the goodness of fit, we can see that the evidence is strongly in favor of the range 0.06~0.08 for the elasticity of TFP to R&D in the period between 1970's and the early 2000's.

In addition, we can say that the decrease of the estimated random coefficient in the middle 1970's, the middle 1980's and the late 1990's shows the offset effect.

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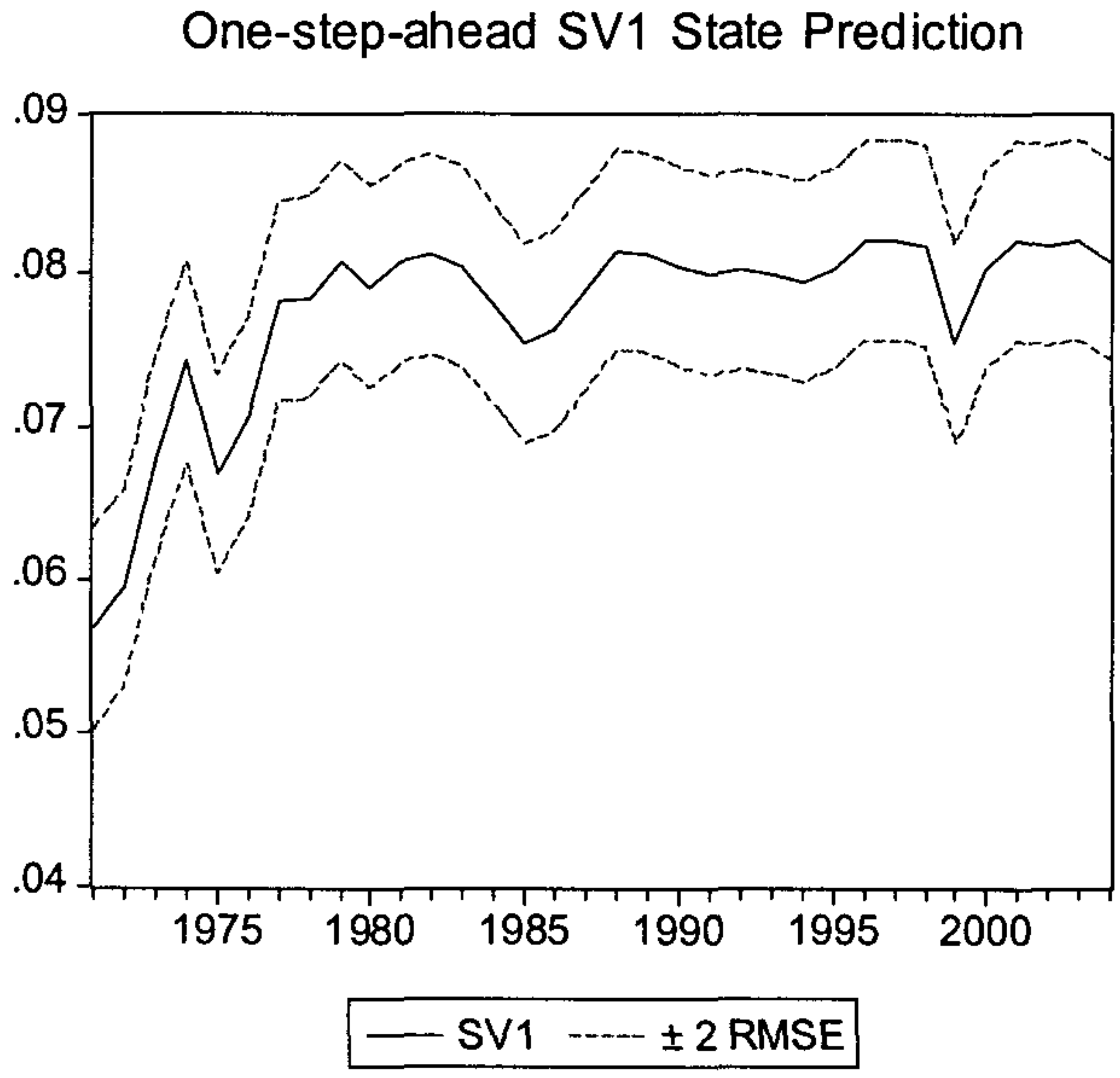
9) One might worry about the lags associated with R&D. But, the basic tool used to deal with the state space model is the Kalman filter, a recurcive procedure for computing the estimator of the unobserved component or the state variable at time t, based on available information at time t. When the shocks are normally distributed, the Kalman filter enables to the likelihood function to be calculated via the prediction error decomposition.

10) We consider the way of making inferences about β(=SV) conditional on information available up to time t. If some of hyperparameters[c(1), c(2)(=σ^2)] are not known, they have to be estimated first before making inferences on β.

〈Table 3〉 Estimation Results for Elasticity of Productivity to Total R&D Flow (Random Coefficient)

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	12.851	0.043	296.518	0.0000*
C(2)	-11.487	0.192	-59.770	0.0000*
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.081	0.003	25.149	0.0000*



(Figure 2) Estimate for Elasticity of Productivity to Total R&D Flow

This model can be expressed as linear state space representation of the dynamics of the unemployment rate Z by the system of equations:

Signal equation:

$Z_t = \gamma + C_t x + u_t$

C_t : unobserved variable(time-varying coefficient: elasticity of R&D)

x : R&D investment flow

State equation:

$C_t = C_{t-1} + \eta_t$

3. Time-varying Random Coefficients Model: R&D Stock

In the basic model of the endogeneous growth model, R&D stock is proportional to the amount of output devoted to R&D, that is, $\Delta T = (1/\eta)(R\&D)$, where η is the amount of R&D required to achieve a unit increase in T. The measured TFP growth rate in equation (3) therefore satisfies

$$(\Delta A/A) = \lambda + \rho(\Delta T/Y) \tag{5}$$

$$(\Delta A/A) = \lambda + \rho\ (R\&D/Y) + \varepsilon \tag{6}$$

where ρ is the rate of return to R&D, ε is disturbance term, and R&D is the R&D stock.

We examined a simple model of the productivity for technical innovation represented by R&D stock:

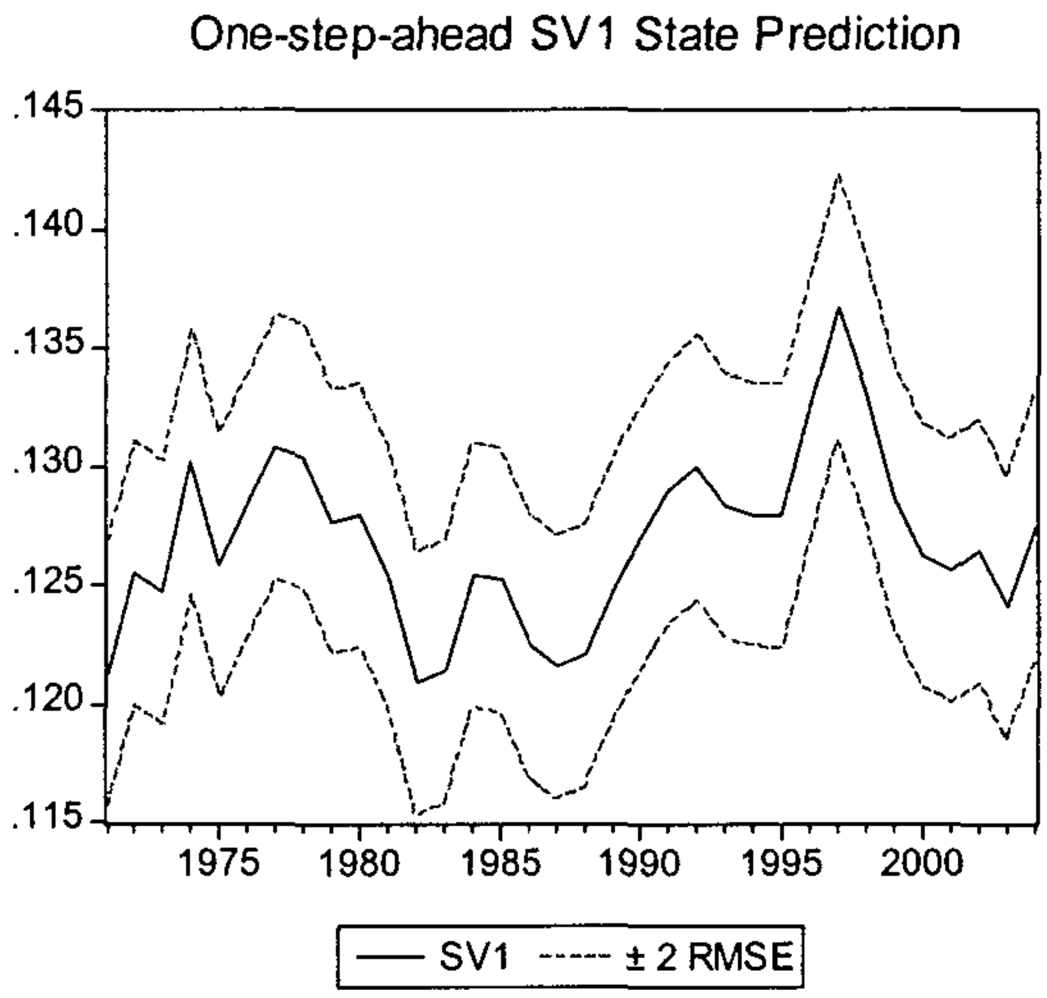
$$\log(A_t) = \alpha + \beta_t \log(RD_t) + \varepsilon_t$$

RD_t: total R&D stock

Estimation (considering autocorrelation of parameter) produces the following results in ⟨Table 4⟩. Estimated standard errors are given together. Considering the goodness of fit, we can see that the evidence is strongly in favor of the range 0.12~0.135 for the elasticity of TFP to R&D stock in the period between 1970's and the early 2000's.

⟨Table 4⟩ Estimation Results for Elasticity of Productivity to total R&D stock (Random Coefficient)

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-0.602	0.288	-2.088	0.0368*
C(2)	-11.770	0.336	-35.064	0.0000*
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.125	0.003	44.854	0.0000*



(Figure 3) Estimate for Elasticity of Productivity to Total R&D Stock

For the estimate for state variable(R&D efficiency estimate), the simple correlation between R&D efficiency(ρ) and some macroeconomic data are listed in ⟨Table 5⟩. As is clear from the table, there are some correlation relation between the efficiency and per GDP(AVERAGEY), human capital(HC), physical capital(K), trade volume(TRADE) and wage level(WAGE). From this, we can infer that economic growth and the openness of the economy are related with R&D efficiency in Korea.

⟨Table 5⟩ Correlations of R&D efficiency with Macroeconomic Variables[11)]

CORR	R&D efficiency(ρ)
AVERAGEY	0.43
HC	0.37
INFLA	0.13
K	0.39
LH	0.27
REALR	-0.13
TRADE	0.42
WAGE	0.39

11) REALR and INFLA denote the rate of real interest and the rate of inflation, respectively.

Ⅳ. Summary and Limitations

In this paper, we need to provide equation dynamic system for productivity and innovation in Korean economy in state space form. State space models have been applied in the econometrics literature to model unobserved variables: the efficiency of R&D stock to productivity. Estimation produces some results. Considering the goodness of fit, we can see that the evidence is strongly in favor of the range 0.120~0.135 for the elasticity of TFP to R&D stock in the period between 1970's and the early 2000's.

Meanwhile, a number of studies have employed traditional growth accounting methods to study the effect of R&D on growth: Zvi Griliches(1988) and the US Bureau of Labor Statistics(BLS)(2000). Most of these studies report a fairly small accounting contribution of R&D to growth, on the order of 0.2 percentage points per year.

In traditional growth accounting, R&D is treated as a second kind of capital investment: an R&D capital stock is constructed by cumulating past expenditures on R&D. The contribution of R&D to growth is then measured by the factor share of R&D multiplied by the growth rate of the stock of past expenditures. Assessing the impact of R&D on growth in this framework then involves measuring the social return to R&D and the net investment rate. A large number of studies have attempted to estimate these quantities, leading to a wide range of estimates.

Grililiches(1988) and the BLS(1989) study report social rates of return to R&D of 20 to 50 %, or even higher; as a benchmark, the BLS chooses a value of 30%.[12] The ratio of R&D expenditures to GDP in the US is measured to be around 2 or 2.5%. Assuming no depreciation of R&D capital, this leads to a growth accounting contribution of anywhere between 0.4 and 1.25 percentage points per year.[13]

The study in this paper reports (social) rates of return to R&D of 17.6 to 43.8 %

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12) Grililiches(1991) finds social rates of return on the order of 40 to 60 %, far exceeding private rates of return.

13) If we know the rate of return of R&D and R&D intensity, we can infer the contribution of R&D for growth of output.

in Korea. The ratio of R&D expenditures to GDP in Korea is measured to be around 3.22%. Assuming no depreciation of R&D capital, this leads to a growth accounting contribution of anywhere between 0.53 and 1.31 percentage points per year.

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서울대학교에서 경제학 학사 및 박사학위(학위논문: 전력시장의 시장지배력)를 취득하고 현재 과학기술정책연구원 부연구위원으로 재직중이다. 주요 연구분야는 경제성장론, 기술경제학, 산업조직론, 응용계량경제 등이며 R&D정책제안을 통해 과학기술발전 및 이를 통한 성장전략 수립에 기여하고 있다.

〈Appendix〉 Elasticity of Direct and Indirect R&D Stock

Generally, the literature distinguishes between the private return of R&D and the social return of R&D. The latter mitigates measurement problems and capture spillovers by focusing on the industry-level data. In firm-level data, measurement errors are important. In this paper, if innovations are used in the same industry, data aggregation to the whole economy-level mitigates these problems. Previous study shows that, when the broadest concept of return is employed in Korea, estimates of the (social) elasticity average about 32(%)[=14(own)+18(used)].(Kim and Lee, 2003) See 〈Table〉.

〈Table〉 Estimation Results for the Elasticity to Direct and Indirect R&D Stock(Flow): Dependent Variable(labor productivity)[14]

Variable	Coefficient	t-Statistic
Constant	-0.037	-1.56
Capital	0.347	3.01*
Own R&D	0.145	2.95*
Used R&D	0.173	2.32**
Scale Variable	-0.005	-0.05
Trend Variable	0.001	3.21*
Adj. R^2	0.31	

14) Kim and Lee (2003), BOK.