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Research on the Effect of Knowledge Stock on Technological Advance and Economic Growth in Republic of Korea

Jaeho Jung [1] and Sangok Choi [2,*]

[1] Korea Institute of Science and Technology Information, Seoul 02456, Republic of Korea; jhjung03@kisti.re.kr
[2] Program in Science and Technology Studies (STS), Korea University, Seoul 02841, Republic of Korea
* Correspondence: sangchoi@korea.ac.kr

Abstract: The Republic of Korea's R&D investment has been rapidly increasing over the long term. This R&D investment is accumulated as knowledge stock, which means the amount of knowledge held by individual countries. However, is the rapid increase in R&D investment contributing to the advancement of domestic science and technology and economic growth? In general, technological advance will lead to a country's sustainable economic growth. If so, how much has it contributed? This is a very important question for a neoclassical economist. This study reviewed previous studies on "knowledge stock", "TFP estimation", and "R&D investment, TFP and economic growth relationship", and sequentially analyzed the relationship among knowledge stock, TFP, and economic growth through a three-step process. The analysis procedure first performs data processing and time series trend analysis, then time series characteristics analysis, and finally Orderful Least Squares (OLS). The analysis results showed that all three models had a positive (+) relationship and most of them were derived to be statistically significant. On this basis, three policy implications are presented. First, the knowledge stock is estimated to have had a positive (+) effect on economic growth, and the continuous increase in domestic R&D investment is believed to have acted as a growth engine. In particular, financial of the government by financial resources and the mid-to-high tech industry groups by industrial characteristics are statistically positively significant. Next, domestic knowledge stocks have had a positive effect on TFP but the efficiency is judged to be decreasing. It is implied that high-tech industries need to form knowledge stocks above the threshold through continuous R&D investment. Finally, TFP was analyzed to have had a high impact on economic growth, and this confirmed that innovation-led growth was important. It is still relevant that innovation-led sustainable growth is more important than factor led in the Republic of Korea.

Keywords: R&D stock; growth accounting; TFP (total factor productivity); economic growth

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1. Introduction

R&D investment in the Republic of Korea has shown a long-term trend of rapid increase. The Republic of Korea's R&D investment began to increase rapidly from the 1980s, and is ranked at the top of the world in terms of size and proportion to GDP. It increased dramatically from KRW 211.7 billion in 1980 (0.54% of GDP) to KRW 89.1 trillion in 2019 (4.63% of GDP) (Compound Annual Growth Rate (CAGR), '80~'19 = 16.3%). As of 2019, the Republic of Korea ranks fifth in the world in total R&D expenses. In particular, the gross domestic expenditure on research and experimental development (GERD) as a percentage of GDP is 4.63%, the second largest in the world (Israel is top ranked in the world 5.14%). This is significantly higher than the OECD average of 2.52% and the European average of 2.11%. The average of surveyed by the OECD is only 1.81% (Figure 1).

In addition, after the financial crisis, R&D investment in the private sector has accelerated further, far exceeding the government R&D investment. As of 2019, the total R&D cost of about KRW 80 trillion consists of approximately KRW 19 trillion (21.8%) by the government and KRW 68.5 trillion (78.2%) by the private sector. This can be interpreted

as a series of efforts to transition from "Factor-Led" to "Innovation-Led" growth after the Asian financial crisis (Krugman, 1994 [1], Young, 1995 [2], Jeong, 2017 [3]). Factor Led means economic growth by labor (L) and capital (K). On the contrary, Innovation Led means economic growth through technological advance (A). This is a very important point. This is because when growth by labor (L) and capital (K) reaches its limit, economic growth begins to occur only by technological advance (A). For this reason, developed countries value growth due to technological advance (A) and input from R&D investment. Finally, technological advance (A) will lead to a country's sustainable economic growth.

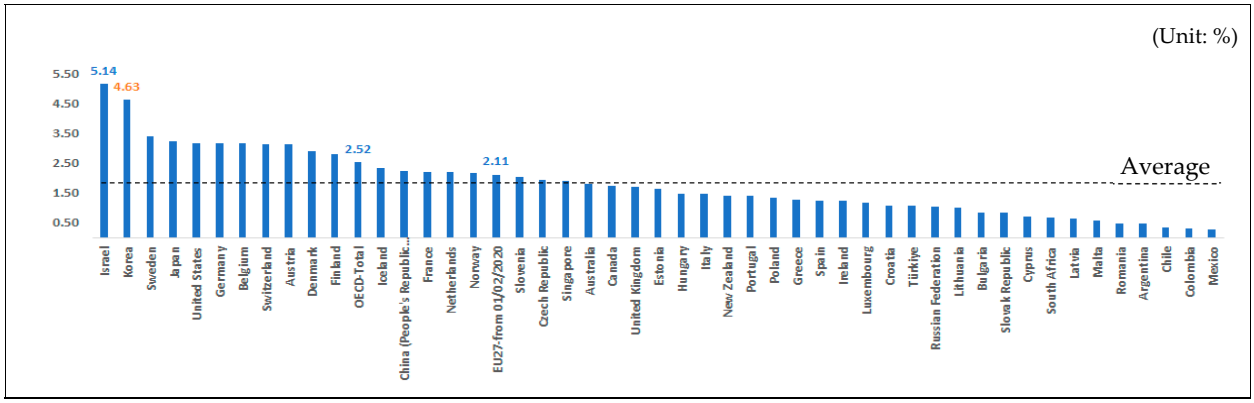

Figure 1. GRED as a percentage of GDP (2019) [4]. Source: OECD Science, Technology and Innovation Scoreboard (https://www.oecd.org/sti/scoreboard.htm accessed on 10 April 2023).

It is generally known that R&D investment is a strong determinant of the advance of science (Jorgenson and Griliches, 1967 [5]). They recognized that when aggregating labor (L) and capital (K) as production factors, production factors put into R&D programs for the advance of science were included. However, as R&D expenditure increases rapidly, questions about the effectiveness of R&D investment continue to be raised. The question is, "Is the rapid increase in R&D investment actually contributing to the advancement of domestic science and technology and economic growth? If so, how much has it contributed?" This is a fundamental question, which can be answered using the growth accounting model of Solow, a neoclassical economist. This model is most commonly used to estimate the contribution of R&D investment to economic growth. It uses the Cobb–Douglas production function to estimate the contribution of labor stock (L), capital stock (K), and technological advance (A) to economic growth rates such as GDP or value added (VA). Technological advance (A) estimates the remaining concept, namely total factor productivity, excluding the contribution rates of labor and capital in the economic growth rate.

However, while there are numerous studies on the estimation of total factor productivity in both domestic and foreign studies, the analysis results obtained by each researcher varied from one another because the method of measuring each variable was different. Theoretical consensus has not been reached on how to estimate labor stocks, labor contribution rates, and capital stocks, and the TFP estimation results are different. As a result, there are also differing results regarding the rate at which technological progress contributed to economic growth in Korea (Table 1). Therefore, it is necessary to secure stability in the results by estimating the TFP and estimating the contribution to economic growth through data and measurement methods widely used domestically and abroad. Accordingly, this study utilizes data from Penn World Table (PWT) overseas and from the Korea Productivity Center (KPC), a domestic institution. Both institutions periodically update and provide data on labor stocks, capital stocks, labor contribution rates, and capital contribution rates.

Although the importance of technological advance is emphasized in industrial policy, there has not yet been sufficient analysis of the contribution of R&D investment at the industrial group level. In regards to industrial policy, there has recently been an emerging emphasis on "True Industrial Policy (TIP)", which had previously been excluded by tradi-

tional economists (Cherif and Hasanov, 2019 [6]). TIP stands for Technology and Innovation Policy, which has three characteristics. First, it supports the domestic producers of high-tech industries beyond the existing comparative advantage. Second, it is export-oriented beyond the limited domestic market; and finally, it pursues intensifying competition rather than industrial protection.

However, there have been almost no studies analyzing the effectiveness of the industrial group considering the technical characteristics of R&D investment. Most existing studies analyzed the economic growth effect of R&D investment at the national or corporate level. In particular, analysis at the industry unit level requires analysis based on the listing of large classification units according to the standard industry classification, and there is a need for a study analyzed based on the characteristics of each field of science and technology (Hwang et al., 2020 [7]). This is because the knowledge stock differs due to the differences in R&D growth rates and obsolescence rates according to the classification by industry group, based on the technology intensity.

In this context, this study is about answers more specifically focusing on the following sequential research questions. What is the contribution rate of domestic R&D investment to technological progress (TFP) and economic growth (GDP, value added) from a long-term perspective? In addition, how much are the differences in the contribution rates to economic growth by each financial resource (government, private sector) and industry group (high technologies, high-to-med tech, med-to-low tech, low tech)? In addition, what is the rate at which technological progress (TFP) contributes to economic growth?

Table 1. An analysis of R&D contribution to growth in previous research in the Republic of Korea.

Sort	Period	Range	Contribution to R&D (%)
STEPI (2004) [8]	1981~2002		28.1
Ha (2005) [9]	1991~2000	Nation	10.9
Shin et al. (1996) [10]	1981~1994	(Total Industry)	34.9
Moon and Lee (2004) [11]	1991~2002		23.3
Kim (2006) [12]	1983~2004	Nation (Total and Manufacturing Industry)	45.7/17.5
Baek(2014) [13]	2004~2008	Nation (Total Industry)	41.3
Park et al. (2016) [14]	1997~2013	ICT Industry	48.2

2. Materials and Methods

2.1. Theoretical Background

2.1.1. Concepts and Estimates of Knowledge Stocks

Knowledge stock is defined as the "stock of information technically useful to facilitate future innovation as a company (industry, country)" that is "directly used in actual production activities" (Chang et al., 1994 [15], STEPI, 2002 [16]). In order to estimate the impact of technological progress on economic growth, it is first necessary to be able to quantitatively measure the amount of technology held. This is a concept similar to capital stock and measures the total amount of stocked knowledge and experience as well as the R&D flow for the current year. Figure 2 explains the difference between the concept of flow and stock of R&D investment. In flow, the technology innovation capability is "t-stage R&D investment (Z)", but in stock, the technology innovation capability is "t-2, t-1, and t-stage R&D investment (X+Y+Z) − obsolescence (δ)')".

Knowledge stock uses the "base year access method", a method of estimating capital stock. As shown in the formula below, it is derived as the sum of the R&D investment for the relevant year and the R&D investment for the previous year in consideration of the obsolescence rates. The obsolescence rate differs according to the nature of R&D investment, financial resources, and industrial characteristics.

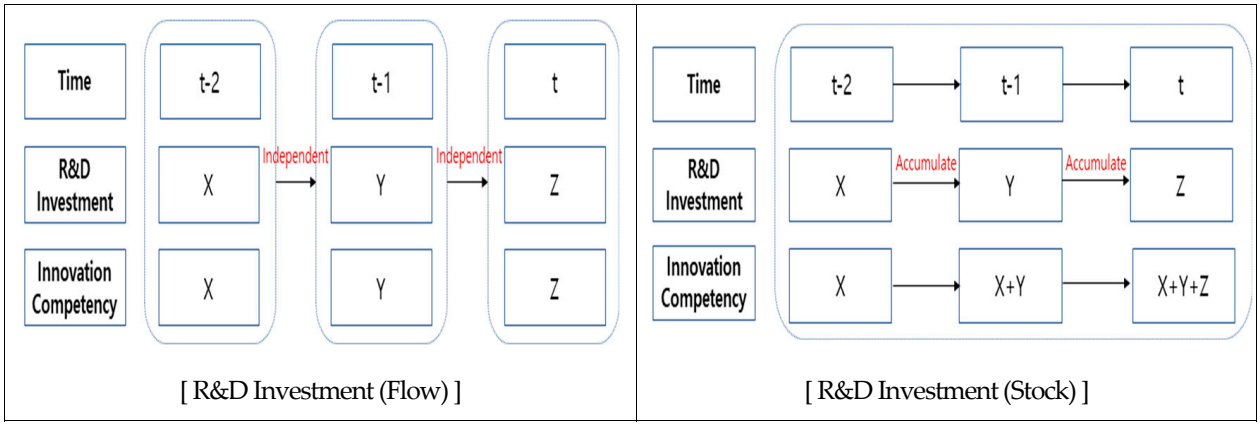

Figure 2. Differences in the concept of flow and stock of R&D investment.

$$RK_t = RI_t + (1 - \delta)RK_{t-1}$$
$$RK_t = \textit{Knowledge Stock},\ RI_t = \textit{The Specific Year R\&D Investment}$$
$$RK_{t-1} = \text{The Previous Specific Year Knowledge Stock},\ \delta = \textit{Obsolescence Rate}$$

The initial knowledge stock is derived using the permanent inventory method. It is "Past Real R&D Investment Considering Depreciation (RI0-i, i = 0...)". It can be defined as the sum of (j), and if the RI increases to a constant g per year, the following occasional (2) can be derived. To summarize Equation (2), the initial knowledge stock can be derived as a value obtained by dividing the product of the initial R&D investment and R&D growth rate by the sum of the R&D growth rate and the obsolescence rate. Taken together, the knowledge stock is determined by the R&D investment growth rate (g) and the advancedization rate (δ).

$$RK_0 = \sum_{i=0}^{\infty} RI_{0-i}(1 - \delta)^i \quad (1)$$

$$RK_0 = RI_0 \sum_{i=0}^{\infty} (1 + \delta)^i (1 + g)^{-i} \quad (2)$$

$$RK_0 = RI_0(1 + g)/(g + \delta) \quad (3)$$

$$RK_0 = \textit{Early Knowledge Stock},\ RI_0 = \textit{Early R\&D Investment}$$
$$g = \textit{R\&D Investment Rate of Increase},\ \delta = \textit{Obsolescence Rate}$$

2.1.2. Technological Innovation and Sustainable Economic Growth

In the neoclassical growth model, technological progress promotes growth in a normal state by improving the quality of labor input. The neoclassical growth model can be typically explained through the production function of Solow(1956) [17], which quantitatively measures the relationship between technological progress and economic growth. Basically, the production function emphasizes the importance of capital accumulation, and the savings rate (investment), population growth, and depreciation cause changes in capital (4). However, if the economies of individual countries reach a point where steady-state savings match the investment needed to supplement labor growth and depreciation, economic growth remains at the level of population growth (5). In response, Solow claims that continuous economic growth will occur as technological advance (A) affects the quality of labor (6). This is referred to as a labor augmenting technological advance (7) and (8).

$$Y = F(K, A\,L) \quad (4)$$

$$\theta = \frac{\Delta A}{A} \quad (5)$$

$$n + \theta = \frac{\Delta AL}{AL} \quad (6)$$

$$y_e = f(k_e) \tag{7}$$

$$\Delta k_e = sy_e - (n + \delta + \theta)k_e \tag{8}$$

Y = *Product*, K = *Capital*, L = *Lablr*, A = *Technology*
Δk_e = *Change in Capital per Unit of Efficiency Labor Input*
y_e = Efficiency Unit Production Per Labor Input Unit

Unlike neoclassical propagation, the Endogenous Growth Theory inputs technological progress as an endogenous variable and presents the progress factors. Romer (1990) [18] defined technology (A) as an idea from the past to the present, that is, knowledge stock. As a factor that constitutes an idea, knowledge stock is defined as the product of the "number of people trying to discover new ideas (L_A)" and the "rate of discovering new ideas (θ)". If the research manpower (L_A) is constant, the rate (θ) of new idea discovery is proportional to the pre-developed idea stock ($A\varphi$). Eventually, the redundant research by the people seeking to discover ideas will be included in the function and this will hinder the formation of knowledge stocks (Duplicate Study (λ) Parameters). Romer thus provides a model that presents technological personnel, the weight of ideas, and duplicate research as important factors that determine technological progress.

Lucas (1988) [19] considers the process of accumulating human capital as an important factor in technological progress. The output (Q) is determined by physical capital (K), human capital (H), and labor input time (u). The physical capital (K) is a value excluding the consumption level in production and does not consider depreciation. The human capital (H) is determined by improving educational productivity through the educational system. Taken together, Lucas emphasizes the importance of human capital, and provides a model in which the education system determines the level of human capital and considers technological progress as a factor.

TFP is generally described as a technological advancement, and has been estimated by a number of researchers. TFP is estimated to be a residual that is not explained by the labor (L) growth rate and the capital (K) growth rate in the economic growth rate. This means that economic growth of a country is achieved by labor, capital, and technological advance. In general, technological advance will lead to a country's sustainable economic growth. According to the formula below, the remaining contributions are estimated from the growth rate of the relevant economic entity (country or company, etc.) excluding labor contributions (labor growth rate × labor contribution rate) and capital contributions (capital growth rate × capital contribution rate). However, there is no empirical agreement with the theory on the measurement of labor and capital stock and the measurement of labor and capital contribution rates in the method of deriving TFP.

$$TFP = \dot{Q} - [(S^L * \dot{L}) + (S^K * \dot{K})]$$

TFP = *Total Factor Productivity*, $\dot{Q}$ = *Economic Growth Rate* , $\dot{L}$ = *Labor Growth Rate*, $\dot{K}$ = *Capital Growth Rate*, S^L = *Labor Contribution Rate*, S^K = *Capital Contribution Rate*

2.2. Literature Reviews

Regarding the higher theories, this section reviews previous studies on "knowledge stock", "TFP estimation", and "R&D investment, TFP and economic growth relationship" (Table 2).

First of all, in the case of knowledge stocks, preceding studies were conducted with a focus on the obsolescence rate and estimation methodology, and the studies by Lee and Kim (2004) [20], Seo (2005) [21], Bosworth (2005) [22], and OECD (2015) [23] were examined. Adopting the most common method, Lee and Kim (2004) [20] estimated knowledge stocks using the "base year access buck" and "permanent inventory method", and calculated the obsolescence rate by major industry using STEPI's innovation survey (Shin et al., 2002 [10]). The obsolescence rate by industry was 0.28 for food and beverage, 0.30 for fiber paper, 0.22 for pulp paper, 0.21 for non-metallic minerals, 0.25 for primary metal, 0.24 for assem-

bly metal, 0.22 for electric electronics, 0.30 for video sound, and 0.26 for transportation equipment. On the other hand, Bosworth (2005) [22] calculated the obsolescence rate of technology knowledge from 1934 to 1965 based on the number of remaining patents. He found a gradual increase in the rate of obsolescence from 10.79% in 1934 to 13.96% in 1965. Similarly, the OECD (2015) [23] suggests the concept and estimation of R&D flows and stocks. In a study that attempted a new methodology, Seo (2005) [21] estimated the obsolescence rate and economic effect in the manufacturing (large category) unit to estimate the return on R&D investment. This study established panel data (695 companies, 8 years) and estimated the obsolescence rate of knowledge stocks using the Klette model. The Klette model is a method of estimating the return using R&D investment as an explanatory variable and calculating the obsolescence rate through the estimated result. As a result, the obsolescence rate by industry was estimated to be food and fiber 0.2495, chemical 0.4302, pharmaceutical 0.4478, metal and steel 0.1160, machinery 0.3135, automobile 0.3115, electric and electronic 0.2674, and service 0.4949. In this study, the concept and estimation method of knowledge stock by the OECD (2015) [23] and Lee and Kim (2003) [20] were used.

Next, to review preceding studies on TFP estimation, we examined the studies of Kim (2017) [24], Kwak (2007) [25], and Krugman (1994) [1]. Krugman (1994) [1] pointed out that growth is not caused by innovation-led growth due to the increase in TFP, but by the input of factors such as labor and capital. This study was conducted using a case analysis method, and it was a pioneering study that predicted the 1997 foreign exchange crisis in East Asia and Young (1992) [2] re-recognized the importance of TFP. While Solow established a theoretical basis for TFP estimation, TFP research began in earnest after Krugman's research. Kwak (2007) [25] estimated the TFP growth rate by industry (agricultural, mining, manufacturing, electric gas water supply, construction, food accommodation, transportation, warehouse, telecommunications, finance, insurance, real estate, social and personal services) from 1970 to 2005. The TFP was estimated to be the value obtained by subtracting the contribution rate of "labor input + human capital + material capital" from the growth rate of GDP by industry, and the results indicated that the Republic of Korea's TFP was generally slowing down (32% in the 1980s, 1.78% in the 1990s, and 1.48% in the 2000s). Kim (2017) [24] presented a method of measuring the TFP by industry and company, and estimated the TFP according to large, medium, and small classifications. This study calculated the TFP level by applying the superlative index method according to the methods of Caves et al. (1982) [26] and Griffith et al. (2004) [27]. As a result, the TFP of the large classification was estimated to be 1.14% for all industries and 3.15% for manufacturing. Meanwhile, in the medium classification, the estimates were 2.83% for the total and 5.54% for the leather, bag, and shoes industries. The lowest estimate was −2.94% for the first steel products. In addition, the total factor productivity by company size was estimated to be 3.62% for more than 10 workers, 3.83% for small and medium-sized enterprises, and 3.95% for large enterprises. In this study, the TFP estimation method by Young (1992) [2] and Kim (2017) [24] was the most used.

Finally, we will focus on recent studies on R&D investment and TFP and economic growth. Cherif and Hasanov (2019) [6] emphasized the importance of technology innovation policy as an industrial policy, and qualitatively explained the theoretical background, characteristics, and history of technology innovation policy as a true industrial policy. This study suggested support for domestic producers of high-tech industries beyond the existing comparative advantage, export orientation beyond the limited domestic market, and pursuing the intensification of competition under strict responsibility rather than the protection of specific industries (or companies). Hwang et al. (2020) [7] estimated the contribution rate of R&D investment to economic growth based on data from 1995 to 2017. In this study, the contribution of R&D investment to economic growth was estimated to be 42.91% (elasticity = 0.132). However, there is a difference between the period and contribution. However, there were differences of contributions across periods, estimated by dividing the proportion of government funds in the total contribution. The contributions by period were as follows: 1995–1997 = 24.16%, 1998–2000 = 8.4%, 2001–2010 = 30.21%, and

2011–2017 = 38.46%. Kim (2020) [28] estimated the relationship between TFP and economic growth through OECD panel analysis, panel analysis by time series and industry in the Republic of Korea, and panel analysis by technology in the Republic of Korea. The TFP estimation method used was similar to that of Kim(2017) [24]. The OECD panel analysis was conducted in 36 countries, and it was estimated that the TFP had a positive (+) effect on labor productivity and R&D intensity. In the analysis of South Korean time series and panels by industry, it was estimated that the R&D intensity had a positive (+) effect on the TFP during the period from 2003 to 2017. In addition, in the panel analysis (6T) by technology in the Republic of Korea, it was estimated that R&D investment had a positive (+) effect on domestic patent applications during the period 2004–2017. In this study, a causal relationship of R&D, TFP, and Economic Growth by the OECD (2015) [23], Cherif and Hasanov (2019) [6], and Kim (2020) [28] was the most used.

Table 2. Summary of major literature reviews.

Sort	Author	Methodology	Main Contents
Knowledge Stock	Bosworth (2005) [22]	Empirical Analysis (Klette Model)	Estimation of R&D Knowledge Obsolescence Ratio
	OECD (2015) [23]	Conceptual and Empirical Analysis	Concept and Estimation of R&D flows and stocks
	Lee & Kim (2004) [20]	Empirical Analysis (Obsolescence of a patent)	Estimation of Productivity Spillover Effect of R&D Investment
	Seo (2004) [21]	Empirical Analysis (Klette model)	Established panel data and estimated the obsolescence rate of knowledge stocks
TFP Estimation	Krugman (1994) [1]	Case Study	TFP Discussion in East Asian Countries
	Young (1992) [2]	Empirical Analysis	Estimating factors for economic growth in Hong Kong and Singapore by growth accounting formula
	Kim (2017) [24]	Empirical Analysis	Methodology of TFP by industry and Firm
A causal relationship of R&D, TFP and Economic Growth	Kafouros (2005) [29]	Empirical Analysis (Constant returns to scale)	Comparison of TFP in the United Kingdom, the United States, France, Germany, and Japan
	OECD (2015) [23]	Conceptual and Empirical Analysis	Estimating R&D returns in the production function framework
	Cherif and Hasanov (2019) [6]	Case Study and Empirical Analysis	Characteristics of Technology and Innovation Policy as a True Industrial Policy (TIP)
	Kim (2020) [28]	Empirical Analysis (Analysis of OECD Panel by Cobb–Douglas production function)	Panel Analysis by Technology in the Republic of Korea
	Hhang et al. (2020) [7]	Empirical Analysis (Estimation to Economic Growth by Cobb–Douglas production function)	Estimating the Effect of R&D Investment on Economic Growth

2.3. Design, Methodology, and Approach

This study aimed to sequentially analyze the relationship between knowledge stock, TFP, and economic growth through a three-step process. First of all, an empirical analysis was conducted on the effect of knowledge stocks on economic growth by industry group,

according to financial resources and R&D intensity. The knowledge stock was estimated using the base year connection method and the permanent inventory method described in the theoretical background. In addition to the total knowledge stock, we estimated the knowledge stock by industry group based on financial resources and R&D intensity. The "financial resource" of knowledge stock refers to the government and the private sector. Based on previous studies, the obsolescence rate was established to be 12.5% for the government and 20.0% for the private sector, and the time lag was not considered for the convenience of research. For knowledge stocks by industry group, industries were classified according to R&D intensity into high-tech, mid-tech, mid-to-low tech and low-tech industries (OECD, 2016) [30]. Based on previous studies, the obsolescence rates were 28.7%, 20.9%, 26.3%, and 29.5%, respectively, and the time lag was not considered for the convenience of research. As for economic growth variables, we used the gross domestic product (GDP) and value added (VA), which were analyzed in most previous studies. These variables used real GDP and VA according to previous studies rather than using GDP and VA per capita (OECD, 2015 [23]; KIET, 2020 [28]). However, in this study we specifically analyzed GDP and VA separately for all industries and manufacturing industries to estimate the impact of knowledge stock on the manufacturing unit. In addition, real standards were applied through the GDP deflator (2015 = 0) provided by the Bank of Korea.

Next, an empirical analysis was performed on the impact of knowledge stocks on technological progress (TFP). We used the data estimated above to obtain the knowledge stock, differentiating the total knowledge stock, knowledge stocks by financial source, and knowledge stocks by industry group according to R&D intensity. TFP was estimated using Solow's growth accounting method. For all industries, we estimated the TFPs for the past 50 years (1970–2019) based on data provided by the Penn World Table (PWT), and for manufacturing industries, we estimated the TFPs for the past 25 years (1995–2018) based on data provided by the Korea Productivity Center (KPC).

Finally, an empirical analysis was conducted on the impact of TFP on economic growth. Analysis was performed using performed using the data we estimated above.

The analysis method followed the procedure of "data processing and time series trend analysis → time series characteristic analysis → OLS." (Table 3)

First, the knowledge stock, TFP, and economic growth variables presented above were processed. Knowledge stocks were estimated through the base year access method using the obsolescence rate by financial resource and industry group. The initial knowledge stock was estimated applying the perpetual inventory method, using the R&D investment growth rate (OECD, 2015 [23]). TFP was estimated using the data on the labor stock, capital stock, labor contribution rate, and capital contribution rate from PWT and KPC. The economic growth variables were collected by dividing all industries and manufacturing industries through the Bank of Korea's economic statistics system and the industrial statistics analysis system, and materialized through the GDP deflator (2015 = 1). The time series trends of knowledge stocks, TFPs, and economic growth variables processed above were analyzed.

Next, a unit root and co-integration test was performed to verify whether the time series data were stationary (Appendix A). In the case of time series data, it was necessary to verify whether the normality is secured in the data, to ensure the reliability of inference statistics. Most time series data are abnormal data with unit roots, and the verification of co-integration is performed. In general, an Augmented Dickey Fuller (ADF) test is performed to test whether the level variable and the difference variable are unit roots, and if there is no unit root in the level variable, it is called I(0), if there is no unit root in the first difference, and if there is no unit root in the second difference, it is called I(2) (Dickey and Fuller, 1976 [31]). In most cases, the unit root is non-existent in I(1) and I(2). Therefore, in this study, the co-integration test was performed by verifying the unit root of the error term of OLS, and verifying the unit root in this verification (Granger, 1981 [32]).

Finally, we performed the OLS analysis with the Error–Correction Model (ECM) of Elgle-Granger (1987) [33]. ECM is a co-integration analysis technique that analyzes OLS through a difference variable when a unit root exists in a level variable. However, in the

case of the difference variable, the error term is input into the OLS equation to estimate the short-term relationship, not the long-term relationship. In other words, a long-term relationship can be estimated by converting an unstable non-stationary into a normal time series through a difference variable and inputting an error term with a first lag. That is, theoretically, ECM is reasonable because it can identify long-term trends in time series. If general OLS is used in this study, only short-term trends in time series are explained. As a result, ECM has been applied in previous studies (Kim, 2017 [24]; KIET, 2020 [34]).

Table 3. Process of methodology and approach.

Process	Methodology	Data Source
1. Data processing and Time series trend analysis	- Base year access method - The perpetual inventory method (OECD, 2015) [23] - Time series trend analysis	- BOK (Bank of Korea) [35] - ISTANS (Industrial Statistics Analysis System) [36] - KPC (Korea Productivity Center) [37] - NTIS (National Science & Technology Information Service) [38] - PWT (Penn World Table) [39]
2. Time series characteristic analysis	- Unit root test (Dickey and Fuller, 1976) [31] - Co-integration test (Granger, 1981) [32]	
3. OLS	- Error–Correction Model (Elgle-Granger, 1987 [33]; Kim, 2017 [24], KIET, 2020 [34])	

3. Results

3.1. Time Series Trend Analysis

The Republic of Korea's knowledge stock has increased rapidly over the past 50 years (1975–2019). The total knowledge stock increased from about KRW 2.4 trillion in 1976 to KRW 1121.4 trillion in 2019 (CAGR = 15.4%), and in terms of financial resources, the private sector's growth rate was estimated to be higher than that of the government. The knowledge stock of the government sector was estimated to be KRW 277.4 trillion in 19 years (CAGR = 12.5%) from KRW 1.76 trillion in 1976, and the knowledge stock of the private sector was estimated to be KRW 844.1 trillion (CAGR = 18.5%) in 1976. In other words, knowledge stocks in both the government and the private sector increased rapidly, and the private sector's growth rate was somewhat high (Figure 3).

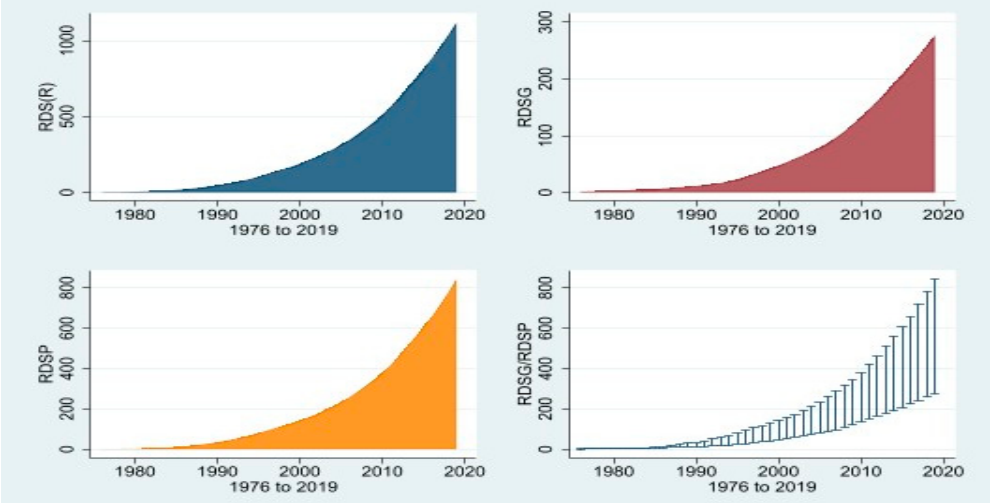

Figure 3. Knowledge stock by financial source (1976–2019). Source: NTIS. Unit: trillion KRW.

Since the 2000s, knowledge stocks by industry group have also been on the rise, mainly in high and middle and high rankings. All four industrial groups increased with an increase rate of around 10%, but in terms of size, the stocks of high and middle- and high-ranking industrial groups increased significantly. The knowledge stock of the high-tech

industry group was estimated to be KRW 99.5 trillion in 2019 from KRW 30.6 trillion in 2004 (CAGR = 8.2%). The knowledge stock of the middle and high-tech industry was estimated to be KRW 83.1 trillion in 2019, increased from KRW 24.4 trillion in 2004 (CAGR = 8.5%). The knowledge stock of the mid–low technology industry group was estimated to be KRW 12.2 trillion in 2019 compared to KRW 3.5 trillion in 2004 (CAGR = 8.7%). The knowledge stock of the low-tech industry group was estimated to have risen from KRW 1.2 trillion in 2004 to KRW 5.9 trillion in 2019 (CAGR = 10.9%). The knowledge stocks of each industry group are all on the rise, but the knowledge stocks of mid-to-high and high-ranking industries have increased significantly (Figure 4).

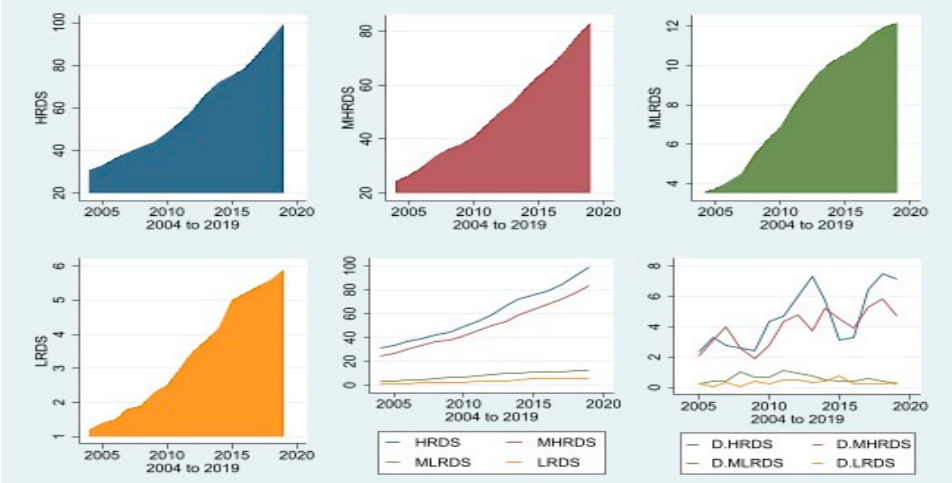

Figure 4. Knowledge stock by industry group based on R&D intensity (2004–2019). Source: ISTANS (unit: trillion KRW).

The Republic of Korea's TFP growth rate has also continued to increase in both across all industries and also specifically in manufacturing over the past 50 years (1970–2019). In particular, the growth rate of all industries (TFP) was estimated to have increased except at certain times such as during the Asian financial crisis of the year 1998. In other words, except for −0.07% in 1980, 0.03% in 1998, and 0.0006% in 2009, the TFP of all industries continued to increase. However, the Republic of Korea's TFP growth rate has been gradually decreasing since the 1990s (1970–1980 = 0.023%, 1980–1990 = 0.037%, 1990–2000 = 0.023%, 2000–2010 = 0.021%, and 2010–2019 = 0.01%). Accordingly, the TFT Index (2015 = 1.0) is continuously increasing, but the slope is gradually decreasing. In other words, the Republic of Korea has continued its technological progress over the past 50 years, but the progress rate is believed to have declined somewhat. This suggests that there may be some problems with sustainable economic growth (Figure 5).

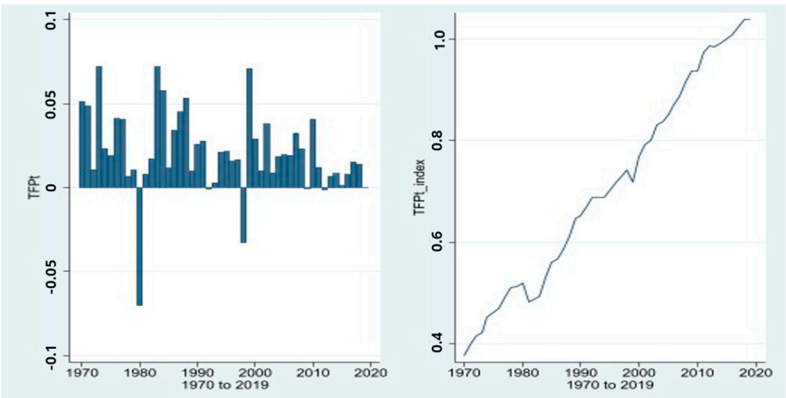

Figure 5. The Republic of Korea TFP and TFP Index (1970–2019, manufacturing industry). Source: PWT version 10.0 (unit: %).

The TFP growth rate of the South Korean manufacturing industry is also on the rise, similarly to the case of all industries. All industries have shown an increasing trend in the TFP growth rate, except for the periods of the 1998 foreign exchange crisis and the 2009 financial crisis, and the manufacturing industry has been no exception. However, the TFP growth rate is gradually decreasing with the time series flow. Accordingly, the slope of the manufacturing industry's TFP Index (2015 = 1.0) is also gradually decreasing. In conclusion, technological progress has also occurred in the manufacturing sector in Republic of Korea, but the progress rate is believed to be on the decline. This suggests that there may be some problems with sustainable economic growth too (Figure 6).

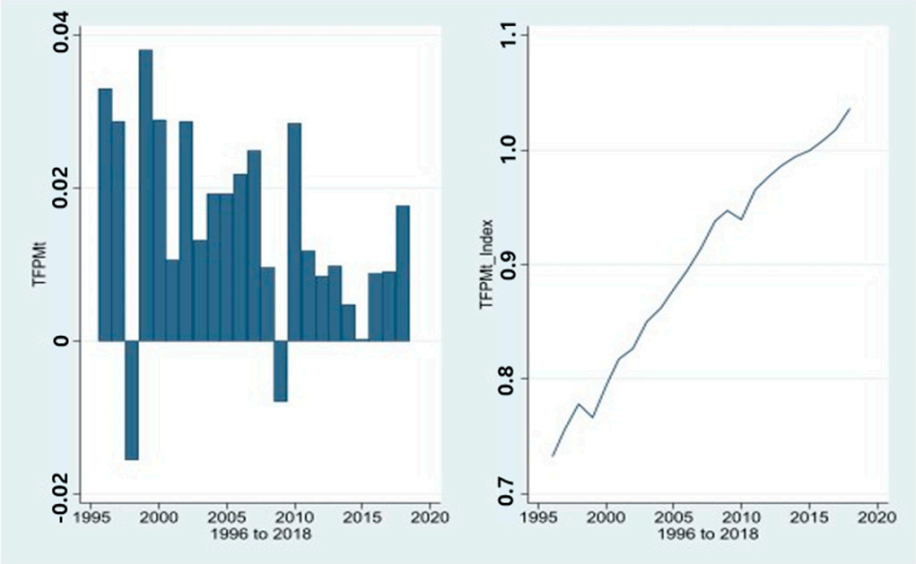

Figure 6. The Republic of Korea TFP and TFP Index (1996–2018, manufacturing industry). Source: KPC (unit: %).

3.2. Analysis of Knowledge Stock, Technology Advances, and Economic Growth

3.2.1. The Impact of Knowledge Stock on Economic Growth

Knowledge stock (1970–2019) was estimated to have a positive (+) effect on the gross domestic product (all industries, manufacturing), but knowledge stock by financial resource was estimated to have a positive effect on the gross domestic product of manufacturing. When the total knowledge stock increased by 1%, it was estimated that the gross domestic product of all industries increased by 0.144% and the gross domestic product of the manufacturing industry increased by 1.636%. However, the knowledge stock by financial source was found to be statistically significant only in the gross domestic product of manufacturing. However, it was estimated that the knowledge stock had a higher impact on the total output of the manufacturing industry compared to all industries (Table 4).

Knowledge stocks were estimated to have a positive (+) effect on the added value, and, in particular, knowledge stocks in the government sector were statistically significant. When the total knowledge stock increased by 1%, it was estimated that the value added of all industries increased by 0.761% and the value added of the manufacturing industry increased by 0.827%. In particular, when the knowledge stock of the government sector increased by 1%, it was estimated that the value added of all industries increased by 0.795%, and the value added of the manufacturing industry increased by 0.838%, and all of them were statistically significant. However, the private sector's knowledge stock did not produce statistically significant results in added value (Table 5).

Table 4. Knowledge stock (finance source) and time series estimation results of gross domestic product.

Variables	(1) ln_GDPt	(2) ln_GDPt	(3) ln_GDPt	(4) ln_GDPMt	(5) ln_GDPMt	(6) ln_GDPMt
ln_Lt	0.602 ***	0.419 ***	0.327 *	−0.909	−0.512	−0.784
	(0.125)	(0.146)	(0.180)	(0.589)	(0.600)	(0.657)
ln_Kt	0.213 **	0.347 ***	0.446 ***	−0.358	−0.237	−0.776
	(0.103)	(0.107)	(0.106)	(0.551)	(0.494)	(1.073)
ln_RDSt	0.144 **			1.636 **		
	(0.0700)			(0.634)		
ln_RDSGt		0.0809			1.197 **	
		(0.122)			(0.442)	
ln_RDSPt			−0.0112			1.909
			(0.0514)			(1.223)
Constant	0.0160 ***	0.0167 ***	0.0175 ***	−0.0631	0.0122	−0.0143
	(0.00531)	(0.00608)	(0.00598)	(0.0372)	(0.0227)	(0.0267)
Observations	147	129	129	84	84	84
R-squared	0.856	0.852	0.856	0.730	0.720	0.705

Note 1. ln_GDPt = gross domestic productivity (all industry), ln_GDPMt = gross domestic productivity (manufacturing), ln_Lt = labor stock, ln_Kt = capital stock, ln_RDSt = knowledge stock, ln_RDSGt = knowledge stock by government, ln_RDSPt = knowledge stock by public. Note 2. Control variable: St = savings rate, It = investment rate, OS = external shock (foreign exchange crisis: 1998, financial crisis: 2009). Note 3. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 5. Knowledge stock (finance source) and time series estimation results of value added.

Variables	(1) ln_VAt	(2) ln_Vat	(3) ln_VAt	(4) ln_VAMt	(5) ln_VAMt	(6) ln_VAMt
ln_Lt	−0.0173	0.192	0.0563	−0.0852	0.143	0.00376
	(0.310)	(0.314)	(0.353)	(0.313)	(0.321)	(0.364)
ln_Kt	0.171	−0.000610	−0.0274	0.143	−0.0161	−0.0148
	(0.453)	(0.401)	(0.759)	(0.448)	(0.407)	(0.775)
ln_RDSt	0.761			0.827 *		
	(0.484)			(0.475)		
ln_RDSGt		0.795 **			0.838 **	
		(0.357)			(0.362)	
ln_RDSPt			0.901			0.912
			(0.822)			(0.846)
Constant	−0.0317	0.00367	−0.000122	−0.0343	0.00391	6.38×10^{-5}
	(0.0278)	(0.0136)	(0.0184)	(0.0277)	(0.0138)	(0.0187)
Observations	84	84	84	84	84	84
R-squared	0.811	0.832	0.811	0.813	0.835	0.810

Note 1. ln_VAt = value added (all industry), ln_VAMt = value added (manufacturing), ln_Lt = labor stock, ln_Kt = capital stock, ln_RDSt = knowledge stock, ln_RDSGt = knowledge stock by government, ln_RDSPt = knowledge stock by public. Note 2. Control variable: St = savings rate, It = investment rate, OS = external shock (foreign exchange crisis: 1998, financial crisis: 2009). Note 3. ** $p < 0.01$; * $p < 0.05$.

Knowledge stocks by industry group were estimated to have a positive (+) effect on the gross domestic product, excluding high-tech industries. In particular, when the knowledge stock of the mid-to-high tech industry increased by 1%, the gross domestic product was estimated to have increased by 0.243%. In addition, when the knowledge stock of the mid-to-low tech and low-tech industries increased by 1%, the gross domestic products were estimated to have increased by 0.093% and 0.12%, respectively. On the other hand, the estimates for the high-tech industry group were found to be statistically insignificant (Table 6).

Table 6. Knowledge stock (industry) and gross domestic product (all industries) time series estimation results.

Variables	(1) ln_GDPt	(2) ln_GDPt	(3) ln_GDPt	(4) ln_GDPt
ln_Lt	0.359	−0.0113	0.166	−0.311
	(0.212)	(0.220)	(0.200)	(0.321)
ln_Kt	1.521 ***	0.827	0.921 *	0.645
	(0.399)	(0.489)	(0.424)	(0.480)
ln_RDSHt	0.155			
	(0.107)			
ln_RDSMHt		0.243 *		
		(0.118)		
ln_RDSMLt			0.0926 *	
			(0.0439)	
ln_RDSLt				0.118 *
				(0.0522)
Constant	−0.0353 *	−0.0140	−0.00643	0.00337
	(0.0158)	(0.0126)	(0.0151)	(0.0173)
Observations	60	60	60	60
R-squared	0.890	0.900	0.922	0.902

Note 1. ln_GDPt = gross domestic productivity (all industry), ln_Lt = labor stock, ln_Kt = capital stock, ln_RDSHt = knowledge stock of high-tech industry, ln_RDSMHt = knowledge stock of mid- to high-tech industry, ln_RDSMLt = knowledge stock of mid-to-low tech industry, ln_RDSHt = knowledge stock of low-tech industry. Note 2. Control variable: St = savings rate, It = investment rate, OS = external shock (foreign exchange crisis: 1998, financial crisis: 2009). Note 3. *** $p < 0.001$; * $p < 0.05$.

Knowledge stock by industry group was estimated to have a positive (+) effect on the total output of the manufacturing industry, excluding the mid- to high-tech industries. Unlike the gross domestic product of all industries, when the knowledge stock of the high-tech industry increased by 1%, the total output of the manufacturing industry was estimated to have increased by 1.456%. In addition, when the knowledge stock of the mid-to-low tech and low-tech industries increased by 1%, the total output of the manufacturing industry was estimated to have increased by 1.13% and 0.65%, respectively. The knowledge stock in the mid-to-low tech industry have a higher positive (+) effect on the total output of the manufacturing industry than all industries. However, the knowledge stock of the mid-to-high tech industry had a positive (+) effect on the total output of the manufacturing industry, but statistically significant results were not derived. Overall, among the knowledge stocks by industry group, it can be judged that the knowledge stocks of the high-tech industries have a higher positive effect than those of the mid-to-low tech and low-tech industries (Table 7).

Table 7. Knowledge stock (industry) and total output (manufacturing) time series estimation results.

Variables	(1) ln_GDPMt	(2) ln_GDPMt	(3) ln_GDPMt	(4) ln_GDPMt
D.ln_Lt	−2.570 **	−2.714 *	−0.967	−3.471 **
	(0.931)	(1.392)	(0.917)	(1.387)
D.ln_Kt	3.630 **	0.563	−0.498	1.069
	(1.401)	(3.198)	(1.839)	(1.476)
D.ln_RDSHt	1.456 **			
	(0.513)			
D.ln_RDSMHt		1.523		
		(1.081)		
D.ln_RDSMLt			1.129 ***	
			(0.200)	

Table 7. *Cont.*

Variables	(1) ln_GDPMt	(2) ln_GDPMt	(3) ln_GDPMt	(4) ln_GDPMt
D.ln_RDSLt				0.644 *
				(0.332)
Constant	−0.190 ***	−0.0883	−0.0309	−0.0388
	(0.0526)	(0.0666)	(0.0681)	(0.0557)
Observations	60	60	60	60
R-squared	0.827	0.703	0.906	0.718

Note 1. ln_GDPMt = Gross Domestic Productivity(Manufacturing), D.ln_Lt = Labor Stock, D.ln_Kt = Capital Stock, D.ln_RDSHt = Knowledge Stock of High-tech Industry, D.ln_RDSMHt = Knowledge Stock of mid-to-high tech Industry, D.ln_RDSMLt = Knowledge Stock of Mid-to-low tech Industry, D.ln_RDSHt = Knowledge Stock of Low-tech Industry. Note 2. Control Variable: St = Savings Rate, It = Investment Rate, OS = External Shock (Foreign Exchange Crisis: 1998, Financial Crisis: 2009). Note 3. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Next, as for the knowledge stock by industry group, it was estimated that the knowledge stock of the high-tech industry group had a high influence on added value. When the knowledge stock of the high-tech industry increased by 1%, the added value was estimated to increase by 0.84%. In addition, when the knowledge stock of the mid-to-low technology industry increased by 1%, value added was estimated to increase by 0.53%. However, the knowledge stock of the mid to low tech industries had a positive (+) effect on added value, but statistically significant results were not derived (Table 8).

Table 8. Knowledge stock (industry) and value-added (all industries) time series estimation results.

Variables	(1) ln_Vat	(2) ln_VAt	(3) Dn_VAt	(4) ln_VAt
D.ln_Lt	−1.269 **	−1.021	0.0521	−1.111
	(0.450)	(0.767)	(0.662)	(0.638)
D.ln_Kt	1.457	0.121	−0.157	0.514
	(0.999)	(2.084)	(0.705)	(1.006)
ln_RDSHt	0.837 **			
	(0.317)			
ln_RDSMHt		0.629		
		(0.652)		
ln_RDSMLt			0.529 ***	
			(0.111)	
ln_RDSLt				0.280
				(0.200)
Constant	−0.0785 *	−0.0197	−0.00890	−0.00895
	(0.0383)	(0.0535)	(0.0358)	(0.0398)
Observations	60	60	60	60
R-squared	0.834	0.732	0.871	0.747

Note 1. ln_VAt = Value Added (all industry), D.ln_Lt = Labor Stock, D.ln_Kt = Capital Stock, ln_RDSHt = Knowledge Stock of High-tech Industry, ln_RDSMHt = Knowledge Stock of Mid-to-High tech Industry, ln_RDSMLt = Knowledge Stock of Mid-to-low tech Industry, ln_RDSHt = Knowledge Stock of Low-tech Industry. Note 2. Control Variable: St = Savings Rate, It = Investment Rate, OS = External Shock (Foreign Exchange Crisis: 1998, Financial Crisis: 2009). Note 3. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Finally, the effect of knowledge stocks by industry group on the added value of the manufacturing industry was derived similarly to the above results. When the knowledge stock of the high-tech industry increased by 1%, the added value was estimated to increase by 0.8%. In addition, when the knowledge stock of the mid-to-low technology industry increased by 1%, the value added was estimated to have increased by 0.55%. However, the knowledge stock of the mid-to-low tech industries had a positive (+) effect on the added value, but statistically significant results were not derived. Overall, knowledge stocks by industry group had a positive (+) effect on the added value, but only high and mid-to-low tech industries were statistically significant. However, it should be noted that the higher the technology intensity, the higher the positive (+) effect on value added (all

industries, manufacturing). It can be judged that there is a positive (+) relationship between the domestic value-added improvement and the technology intensity (Table 9).

Table 9. Knowledge stock (industry) and value-added (manufacturing) time series estimation results.

Variables	(1) ln_VAMt	(2) ln_VAMt	(3) ln_VAMt	(4) ln_VAMt
ln_Lt	−1.264 **	−1.102	−0.161	−1.283
	(0.490)	(0.804)	(0.752)	(0.806)
ln_Kt	1.813	0.125	0.0396	0.755
	(1.024)	(2.157)	(1.127)	(1.193)
ln_RDSHt	0.800 **			
	(0.323)			
ln_RDSMHt		0.787		
		(0.646)		
ln_RDSMLt			0.554 ***	
			(0.112)	
ln_RDSLt				0.304
				(0.214)
Constant	−0.0874 *	−0.0314	−0.0143	−0.0170
	(0.0391)	(0.0498)	(0.0466)	(0.0445)
Observations	60	60	60	60
R-squared	0.830	0.756	0.873	0.756

Note 1. ln_VAMt = value added (manufacturing), ln_Lt = labor stock, ln_Kt = capital stock, ln_RDSHt = knowledge stock of high-tech industry, ln_RDSMHt = knowledge stock of mid-to-high tech industry, ln_RDSMLt = knowledge stock of mid-to-low tech industry, ln_RDSHt = knowledge stock of low-tech industry. Note 2. Control variable: St = savings rate, It = investment rate, OS = external shock (foreign exchange crisis: 1998, financial crisis: 2009). Note 3. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

3.2.2. The Effect of Knowledge Stock on Total Factor Productivity

Knowledge stocks had a positive (+) effect on the increase in TFP, and all were estimated to be statistically significant. With a 1% increase in total knowledge stock, TFP was estimated to have increased by 0.12% over the past 50 years (1970–2019). When the knowledge stock in the government sector increased by 1%, TFP was estimated to have increased by 0.1% over the past 45 years (1976–2019). When the private sector knowledge stock increased by 1%, the TFP was estimated to have increased by 0.04% over the past 45 years (1976–2019). In other words, in terms of elasticity, it is estimated that the knowledge stock of the government sector is more efficient than the private sector. However, it was found that capital stock had the most positive (+) effect on total factor productivity (Table 10).

Next, knowledge stocks by industry group also had a positive (+) effect on the increase in TFP, and all were estimated to be statistically significant. In the past 15 years (2005–2019), when the knowledge stock of high-tech industries increased by 1%, the TFP was estimated to have increased by 0.06%. In particular, when the knowledge stock of the mid-to-high tech industries increased by 1%, TFP showed the highest positive (+) effect at 0.3%. In addition, when the knowledge stock of the mid-to-low tech industries increased by 1%, the TFP was estimated to have increased by 0.08% and 0.07%, respectively. Overall, knowledge stocks by industry group had a positive (+) effect on TFP, but knowledge stocks of mid-to-high tech industries were estimated to have the highest effect. In other words, since the 2000s, domestic technological progress is judged to have had a high contribution of knowledge stocks in the mid-to-high tech industries. On the other hand, the knowledge stock of the high-tech industry group was estimated to have a positive (+) effect, but it was estimated to contribute the lowest to the increase in TFP (Table 11).

Table 10. Knowledge stock (financial source) and total factor productivity time series estimation results.

Variables	(1) TFPt	(2) TFPt	(3) TFPt
ln_Lt	−0.530 ***	−0.457 ***	−0.838 ***
	(0.113)	(0.116)	(0.0861)
ln_Kt	0.204 **	0.211 ***	0.396 ***
	(0.0971)	(0.0658)	(0.0365)
ln_RDSt	0.122 **		
	(0.0526)		
ln_RDSGt		0.104 ***	
		(0.0267)	
ln_RDSPt			0.0406 *
			(0.0213)
Constant	2.472 ***	1.585 **	4.055 ***
	(0.881)	(0.720)	(0.958)
Observations	147	129	129
R-squared	0.984	0.984	0.971

Note 1. ln_TFPt = total factor productivity, ln_Lt = labor stock, ln_Kt = capital stock, ln_RDSt = knowledge stock, ln_RDSGt = knowledge stock by government, ln_RDSPt = knowledge stock by public. Note 2. Control variable: St = savings rate, It = investment rate, OS = external shock (foreign exchange crisis: 1998, financial crisis: 2009). Note 3. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 11. Knowledge stock (industry) and total factor productivity time series estimation results.

Variables	(1) TFPt	(2) TFPt	(3) TFPt	(4) TFPt
ln_Lt	−0.176 ***	−0.295 ***	0.104 ***	−0.140 ***
	(0.0423)	(0.0149)	(0.0225)	(0.0167)
ln_Kt	0.374 ***	−0.238 ***	0.260 ***	0.278 ***
	(0.0472)	(0.0412)	(0.0226)	(0.0259)
ln_RDSHt	0.0575 *			
	(0.0336)			
ln_RDSMHt		0.299 ***		
		(0.0170)		
ln_RDSMLt			0.0826 ***	
			(0.00676)	
ln_RDSLt				0.0745 ***
				(0.00762)
Observations	56	56	56	56
R-squared	0.995	0.998	0.998	0.997

Note 1. ln_TFPt = total factor productivity, ln_Lt = labor stock, ln_Kt = capital stock, ln_RDSHt = knowledge stock of high-tech industry, ln_RDSMHt = knowledge stock of mid-to-high tech industry, ln_RDSMLt = knowledge stock of mid-to-low tech industry, ln_RDSHt = knowledge stock of low-tech industry. Note 2. Control variable: St = savings rate, It = investment rate, OS = external shock (foreign exchange crisis: 1998, financial crisis: 2009). Note 3. *** $p < 0.001$; * $p < 0.05$.

3.2.3. The Effects of Total Factor Productivity on Economic Growth

TFP had a positive (+) effect on economic growth and was estimated to be statistically significant. When the TFP increased by 1%, GDP was estimated to have grown by 0.95 percent over the past 50 years (1970–2019). In addition, when the TFP increased by 1%, the total output of the manufacturing industry was estimated to have grown by 0.95% over the past 30 years (1990–2019). In addition, it was estimated that the increase in TFP 1% increased the value added of all industries by 1.45% and the value added of manufacturing by 1.53%. In other words, TFP showed a large positive (+) effect on the gross domestic product (all industries, manufacturing), and value added (all industries, manufacturing), which are economic growth indicators. It is believed that the TFP growth rate, which has been on a steady decline compared to before the 2000s, can be a factor

explaining the decline and stagnation of domestic economic growth. TFP is believed to have contributed highly to domestic economic growth, and the recent decrease in TFP growth is believed to be related to the stagnation of economic growth. In other words, it appears that the "innovation-driven" growth claimed by Krugman (1994) [1] and Young (1995) [2] can maintain sustainable economic growth more effectively than "factor-driven" growth (Table 12).

Table 12. Total factor productivity and economic growth time series estimation results.

Variables	(1) ln_GDPt	(2) ln_GDPMt	(3) ln_VAt	(4) ln_VAMt
TFPt	0.955 ***	2.145 ***	1.446 ***	1.526 ***
	(0.0145)	(0.750)	(0.410)	(0.405)
ln_Lt	0.507 ***	−0.376	0.226	0.190
	(0.00781)	(0.617)	(0.319)	(0.323)
ln_Kt	0.413 ***	0.669 **	0.636 ***	0.651 ***
	(0.00691)	(0.292)	(0.215)	(0.216)
Constant	0.00333 ***	−0.0140	−0.0155	−0.0162
	(0.000456)	(0.0224)	(0.0138)	(0.0139)
Observations	49	28	28	28
R-squared	0.999	0.722	0.840	0.846

Note 1. ln_GDPt = gross domestic productivity (all industry), ln_GDPMt = gross domestic productivity (manufacturing), ln_VAt = value added (all industry), ln_VAMt = value added (manufacturing), ln_TFPt = total factor productivity, ln_Lt = labor stock, ln_Kt = capital stock. Note 2. Control variable: St = savings rate, It = investment rate, OS = external shock (foreign exchange crisis: 1998, financial crisis: 2009). Note 3. *** $p < 0.001$; ** $p < 0.01$.

4. Discussion

As a result of the analysis, all models showed a positive (+) relationship, and most of them were statistically significant. In Model 1 (Knowledge Stock → Economic Growth), it was estimated that most of the knowledge stocks had a positive (+) effect on economic growth. Model 2 (Knowledge Stock → Technology Advance) also analyzed the relationship between the knowledge stock and technological progress (TFP), and it was estimated that there was a positive (+) effect. Finally, Model 3 (Technology Advance → Economic Growth) analyzed the relationship between technological progress (TFP) and economic growth, and it was estimated that there was a positive (+) effect. Based on the results of this analysis, the following three policy implications can be derived (Table 13).

Model 1 shows knowledge stocks are statistically significant to GDP and value added, which are economic growth variables. All knowledge stocks by financial resource have a positive effect, but the private sector is not statistically significant. Knowledge stocks by industry group all have a positive effect and high and mid-to-high tech industries are estimated to have high elasticity. It means that the knowledge stock was estimated to have a positive (+) effect on economic growth, and the continuous increase in domestic R&D investment is believed to have acted as a growth engine. As discussed in the neoclassical growth model (Solow, 1957) [17], when the economy of individual countries reaches a normal state, technological progress leads to economic growth. In other words, economic growth is determined by knowledge stocks when there is a limit to growth by labor and capital. Although several factors are suggested as a source of technological progress in the theory of endogenous growth, the most basic is the formation of knowledge stocks through R&D investment. The results of the time series trend analysis indicated that the accumulation of knowledge stocks is slow in the early stages of R&D investment, but after a certain period of time, the knowledge stocks rise to a steep slope. This can be confirmed through the phenomenon that the knowledge stock increased despite the decrease in the growth rate of R&D investment since the 2000s. In other words, it can be seen that R&D investment is not accumulated as knowledge in a short period of time, but the concept of stock, which is accumulated over a long period of time such as capital, is important.

Accordingly, the formation of knowledge stocks through continuous R&D investment is expected to serve as the basis for future economic growth.

Table 13. Summary of key findings.

Sort		Result	Main Points
Model 1. Knowledge Stock → Economic Growth	Knowledge Stock → Economic Growth	Significant (+)	Estimate that manufacturing industry is more resilient than total industry
	Knowledge Stock by Financial Resource → Economic Growth	Significant (+)	Most private sector estimates statistically insignificant
	Knowledge Stock by Industry → Economic Growth	Significant (+)	High and high to med industrial groups are highly resilient
Model 2. Knowledge Stock → Technology Advance	Knowledge Stock → Technology Advance	Significant (+)	All knowledge stocks have a positive (+) impact on technology advance
	Knowledge Stock by Financial Resource → Technology Advance	Significant (+)	
	Knowledge Stock by Industry → Technology Advance	Significant (+)	
Model 3. Technology Advance → Economic Growth		Significant (+)	Statistically significant estimates of all, especially manufacturing are more highly elastic than all industries

Model 2, the relationship between knowledge stock and technology advance, was analyzed and it is estimated that there is a positive effect for all variables. It means that domestic knowledge stocks had a positive effect on TFP, that is, technological progress, but it is judged that efficiency is decreasing. The knowledge stock had a positive (+) effect on TFP, but the rate of TFP growth is slowing. This is a phenomenon in which technological progress is gradually decreasing even though the knowledge stock is gradually increasing. This phenomenon can be interpreted as indicating that existing technological advances have a negative effect on future technological advances, as suggested by Romer. In other words, it can be interpreted as a situation in which the creation of new ideas, which are the source of technological progress, is gradually decreasing. In fact, patent applications in the Republic of Korea have been gradually decreasing since 2010. In order to overcome this, a policy direction is needed to strengthen R&D investment in mid-to-high level technology industries that derived a more relatively high elasticity than other industires in TFP. However, as high-tech industries, such as aerospace and bio industries, need to develop state-of-the-art technologies, it is judged that they need to form knowledge stocks above the threshold through continuous R&D investment. This is because knowledge stock has not yet had a high impact on TFP.

Model 3, the relationship between technology advance and economic growth, was analyzed and it is estimated that there is a positive effect, especially in manufacturing, which is more highly elastic than all industries. It was analyzed that TFP had a high impact on economic growth, and this study confirmed that innovation-led growth is important. Therefore, it is still relevant that innovation-led to sustainable growth is more important than factor led in the Republic of Korea. Questions about the rapid growth of East Asia and the financial crisis raised by Krugman (1994) [1] and Young (1995) [2] provided historical implications that technological progress should be the core of economic growth. In the Republic of Korea, innovation growth has recently emerged, caused by more continuous R&D investment than compared to the past. After the financial crisis, the factor of continuous economic growth can be seen as the formation of knowledge stocks through R&D investment. However, as mentioned above, as the growth rate of

technological progress is decreasing, the efficient management of R&D investment is required. According to the model presented by Lucas (1988) [19], the redundancy of R&D investment has a negative effect on technological progress. Currently, the number of R&D investments, projects, and tasks in the Republic of Korea is quite large, but there needs to be closer evaluation of whether they are efficiently managed. This means that there may be some problems with sustainable economic growth. In other words, it is necessary to emphasize the importance of forming knowledge stocks through R&D investment, and at the same time, to check the efficiency of the process of connecting knowledge stocks to technological progress.

5. Conclusions

Overall, we compare the elasticity of this study with the previous research in the Republic of Korea (Table 14). In this study, R&D elasticity was estimated differently according to the analysis period and target, and in particular, the R&D elasticity for added value was estimated to be high. Among recent studies, Hwang et al. (2020) [7] estimated the R&D elasticity to be 0.132, while Park et al. (2016) [14], who estimated only the ICT industry, had an estimate of 0.344. In this study, similar figures were derived: the R&D elasticity on GDP was 0.144 for all industries and 0.118 to 0.243 for industrial groups based on R&D intensity. However, the R&D elasticity on added value was estimated to be higher than that of other studies. This is because other studies basically estimated the relationship between GDP and R&D elasticity. In addition, in this study, labor, capital, and knowledge stocks were input factors, and the savings rate and investment rate that were presented as growth factors in the neoclassical model were input as the control variables. In other words, as additional variables were input compared to existing studies, there is a limit to the direct comparison of the research results.

This study contributes academically by reaffirming the results estimated from previous studies based on the neoclassical growth model and endogenous growth theory, and estimating the economic growth effect of the industry according to the technology group. However, this study has the following limitations. In a growth model, there are many other variables that would exert an effect on growth including trade openness, financial development, and the stock of human capital. Next, TFP is a variable representing technological innovation, but there are other variables that estimate technological innovation. Lastly, panel analysis along with time series data are required to analyze the increase in harvest for the scale discussed in the theory of endogenous growth. Therefore, as a follow-up study, we will supplement these parts and conduct further studies. Especially, international comparative studies will be conducted to the extent that data are allowed.

Table 14. Comparison of the results of this study and major previous studies.

Sort	Period	Range	R&D Elasticity
This study	1976~2019	Total industry (GDP)	0.144
	1991~2019	Total industry (Value added)	0.761
	2005~2019	Industries based on R&D intensity (GDP)	- High Tech (0.155) - Medium–High Tech (0.243) - Medium–Low Tech (0.155) - Low Tech (0.118)
	2005~2019	Industries based on R&D intensity (Value added)	- High Tech (0.837) - Medium–High Tech (0.629) - Medium–Low Tech (0.529) - Low Tech (0.280)

Table 14. *Cont.*

Sort	Period	Range	R&D Elasticity
Hwang et al. (2020) [7]	1995~2017	Total industry	0.132
Beak et al. (2016) [13]	1997~2013	ICT industry	0.344
Kim (2011) [40]	1976~2019	Total industry	0.166

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Appendix A. Analysis Process of ECM (Error-Correction Model) by Engle and Granger

Table A1. Unit root test.

Variable		Level Variable	1st Difference	2nd Difference	Test
ln_RDSt	ADF	−3.057 (0.0299) **	-	-	I(0)
	PP	−2.299 (0.1724)	−2.065 (0.2589)	−6.856 (0.0000) ***	I(2)
ln_RDSGt	ADF	−2.166 (0.2189)	−0.880 (0.7946)	−3.714 (0.0039) ***	I(2)
	PP	−4.815 (0.0007) ***	-	-	I(0)
ln_RDSPt	ADF	−2.507 (0.1138)	−3.556 (0.0067) ***	-	I(1)
	PP	−10.02 (0.0000) ***	-	-	I(0)
ln_Lt	ADF	−3.384 (0.0115) **	-	-	I(0)
	PP	−6.895 (0.0000) ***	-	-	I(0)
ln_Kt	ADF	−3.384 (0.0128) **	-	-	I(0)
	PP	−3.685 (0.0043) ***	-	-	I(0)
TFP	ADF	−1.275 (0.06405)	−2.845 (0.0521) **	-	I(1)
	PP	−1.903 (0.3309)	−6.322 (0.0000) ***	-	I(1)
TFPM	ADF	−2.662 (0.0809) *	-	-	I(0)
	PP	−2.443 (0.1300)	−5.580 (0.0000)	-	I(1)
ln_GDPt	ADF	−2.537 (0.1067)	−0.802 (0.8184)	−4.047 (0.0012) ***	I(2)
	PP	−5.725 (0.0000) ***	-	-	I(0)
ln_GDPMt	ADF	−1.704 (0.4290)	−4.466 (0.0002) ***	-	I(1)
	PP	−1.720 (0.4208)	−4.463 (0.0002) ***	-	I(1)
ln_VAt	ADF	−1.099 (0.7153)	−1.613 (0.4763)	−3.366 (0.0122) **	I(2)
	PP	−2.045 (0.2670)	−5.080 (0.0000)	-	I(1)
ln_VAMt	ADF	−1.026 (0.7438)	−1.577 (0.4953)	−3.214 (0.0192) **	I(2)
	PP	−1.999 (0.2869)	−4.991 (0.0000) **	-	I(1)

Nete 1. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table A2. Covariance test.

Sort	Relationship	Result	Test
Knowledge Stock → Economic Growth	ln_RDSt → GDPt	−3.514 (0.0076) ***	Exist
	ln_RDSGt → GDPt	−3.309 (0.0145) **	Exist
	ln_RDSGt → GDPt	−3.860 (0.0024) ***	Exist
	ln_RDSt → GDPMt	−2.181 (0.2129)	Non-exist
	ln_RDSPt → GDPMt	−2.041 (0.2689)	Non-exist
	ln_RDSPt → GDPMt	−2.238 (0.1929)	Non-exist
	ln_RDSt → VAt	−3.315 (0.0241) **	Exist
	ln_RDSGt → VAt	−3.031 (0.0321) **	Exist
	ln_RDSPt → VAt	−3.163 (0.0222) **	Exist
	ln_RDSt → VAMt	−3.057 (0.0299) **	Exist
	ln_RDSPt → VAMt	−2.941 (0.0408) *	Exist
	ln_RDSPt → VAMt	−3.066 (0.0291) **	Exist
	ln_RDSHt → GDPt	−3.951 (0.0017) ***	Exist
	ln_RDSMHt → GDPt	−2.690 (0.0758) *	Exist
	ln_RDSMLt → GDPt	−3.096 (0.0268) **	Exist
	ln_RDSLt → GDPt	−2.897 (0.0456) **	Exist
	ln_RDSHt → GDPMt	−4.005 (0.0014) ***	Exist
	ln_RDSMHt → GDPMt	−3.471 (0.0088) ***	Exist
	ln_RDSMLt → GDPMt	−4.255 (0.0005) ***	Exist
	ln_RDSLt → GDPMt	−4.375 (0.0001) ***	Exist
	ln_RDSHt → VAt	−4.280 (0.0005) ***	Exist
	ln_RDSMHt → VAt	−4.270 (0.0005) ***	Exist
	ln_RDSMLt → VAt	−4.377 (0.0003) ***	Exist
	ln_RDSLt → VAt	−5.718 (0.0000) ***	Exist
	ln_RDSHt → VAt	−4.368 (0.0003) ***	Exist
	ln_RDSMHt → VAMt	−4.162 (0.0008) ***	Exist
	ln_RDSMLt → VAMt	−5.129 (0.0000) ***	Exist
	ln_RDSLt → VAMt	−6.141 (0.0000) ***	Exist
Knowledge Stock → Technology Advance	ln_RDSt → TFPt	−3.544 (0.0069) ***	Exist
	ln_RDSGt → TFPt	−2.966 (0.0382) **	Exist
	ln_RDSPt → TFPt	−4.017 (0.0013) ***	Exist
	ln_RDSHt → TFPMt	−3.900 (0.0020) ***	Exist
	ln_RDSMHt → TFPMt	−5.034 (0.0000) ***	Exist
	ln_RDSMLt → TFPMt	−4.444 (0.0002) ***	Exist
	ln_RDSLt → TFPMt	−4.132 (0.0009) ***	Exist
Technology Advance → Economic Growth	TFPt → GDPt	−2.501 (0.1153)	Non-exist
	TFPt → GDPMt	−2.187 (0.2111)	Non-exist
	TFPt → VAt	−2.808 (0.0571) **	Exist
	TFPt → VAMt	−2.767 (0.0697) **	Exist

Note. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

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